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# Towards a framework for asset pricing in developing equity markets

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**2021**
University of the Witwatersrand, Johannesburg
https://hdl.handle.net/10539/40886
Ouma, Wycliffe Nduga. (2021). Towards a framework for asset pricing in developing equity markets [PhD thesis, University of the Witwatersrand, Johannesburg]. WireDSpace. https://hdl.handle.net/10539/40886

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# TOWARDS A FRAMEWORK FOR ASSET PRICING IN DEVELOPING EQUITY MARKETS

**Dissertation submitted in fulfilment of the requirements for the award of**

**Doctor of Philosophy (PhD) in**

**Financial Economics**

**Graduate School of Business Administration**

**University of the Witwatersrand**

**Supervisor: Professor Odongo Kodongo**

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**December 2021**

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## Abstract

The need to accurately determine risk-return trade-offs in financial markets is an important question that has occupied minds of various players in capital markets for over five decades now. In this study, we addressed this question by attempting to determine the drivers of returns in developing equity markets. Further, we test the ability of the identified factors to command significant and reasonable risk premiums in the returns of developing equity markets. The results of this analysis were compared with those of a select group of emerging and developed equity markets. This study employed monthly stock price data from 20 developing equity markets, starting January 1, 1996, and ending February 1, 2020, resulting in 290 months of observation. Countries are included in the study as their data became available.

Monthly stock price data were used to calculate individual stock returns for the first phase of the study, which involved determining the covariance matrix of returns. This was done through a dimensionality reduction technique of Asymptotic Principal Components Analysis and standard PCA whenever data permitted. The underlying drivers of returns variations determined through these procedures resulted in a few significant principal components (PCs) driving overall stock variations. The next step related the identified PCs to the candidate risk factors ensuring that empirical testing of asset pricing factors only included factors with important influence on stock variations.

The study has found important empirical results on asset pricing in developing equity markets. First, the study has established that only a few fundamental drivers influence returns in the sampled 20 developing equity markets. At country level, factor identification strategy employed discovered that only a few principal components were significantly related to the covariance matrix of returns. Canonical correlations analysis largely confirmed the results as

factors such as excess market returns, book-to-equity and aggregate volatility significantly influenced returns variations in most of the individual markets in the sample.

The empirical evaluation of the identified factors further established that excess market returns (MKT), book-to-market (value) factor (HML), profitability factor (RMW), momentum factor (UMD), unanticipated inflation factor (UI), aggregate volatility (VOL), and trade weighted US dollar index (TW$) were significantly priced in the returns of developing equity markets. Although FM regression did not price UI and TW$, the associated $t-$statistic of their coefficients were closer to the threshold value of 2. For instance, UI and TW$ respectively produced $t-$stat 1.952 and 1.929, which are significant at the 10% level. The GMM analysis, used for robustness checks, confirmed that MKT, HML, UMD and VOL were significantly priced, but further found that both UI and TW$ were not only significant drivers of risk variations, but also priced in the returns of developing equity markets.

Further, DS-LASSO was used to check the robustness of the entire system starting from the factor identification to testing the identified factors. The results largely corroborate the conclusions of GMM, that MKT, HML, UMD and TW$ significantly explain returns variations of frontier equity style portfolios and are priced. The results also indicated that UI is marginally priced with a $t-$stat of 1.958.

This study puts forward some recommendations. First, we recommend a favourable policy environment to accelerate capital market development and investment in developing countries. Since accounting information has been established to proxy for common pervasive risk drivers in stock markets, financial reporting standard is, therefore, crucial to the quality accounting information disseminated. Developing equity markets need to institute prudent and harmonised accounting practices and strong corporate governance systems to ensure quality reporting. Debt variables such as corporate bonds and government bonds form a significant component of

capital market investment and are important drivers of returns in these stock markets. Unfortunately, developing equity markets do not have well-functioning debt markets rendering the variables irrelevant in their risk-return equation. Thus, these countries should institute deliberate policy measures to ensure growth of debt markets.

## Declaration

This PhD dissertation is my original toil that has not been presented before for a degree in this or any other University.

## Appreciation

Interest in this study spans back to my first ever form of research writing in an undergraduate research project at the Jomo Kenyatta University of Agriculture and Technology in Nairobi. Then my fascination was shaped by an intriguing phenomenon underlying change in stock prices at the Nairobi Stock Exchange (NSE). My form of 'Thesis' titled *"Factors influencing stock performance at the Nairobi Stock Exchange"* remains my launching pad into this long laborious journey.

My fascination with mechanisms propelling changes in stock prices did not end with the first shot at research as the narrow objective did not arrive at an authoritative panacea to my fascination. Armed with more knowledge, tools, and direction, I revisited the subject for Masters Dissertation under the able guidance of Dr. Peter Muriu for whom I remain invaluably indebted. Dr. Peter Muriu made me believe that my somehow inadequate thought process in financial economics is as meaningful and valuable like the revered names in the field. It then dawned on me right away after submitting my thesis that I needed to explore further, deeper, and broader into asset pricing beyond the Nairobi Securities Exchange. I had to go for a PhD on the subject.

Hence, I owe this work to many, but first and foremost the most important human being in my life, my Mamma Alda. If it were not for my mamma, I would never appreciate the rigorous search for knowledge, and the enthusiasm to always keep going, making the inevitable part of my fate. They say God reveals Himself through people and events, my mamma is a true reflection of God in my life journey. I can never thank her enough! Mamma, I am overwhelmingly grateful for the insights, efforts, connections with your colleagues to help me go through these works. I am particularly indebted to the network you created between me and your colleague Prof. Livio Fenga.

Along my PhD journey, greater blessings emerged, my adorable little man, Hekima came along, and now my adorable Princes Hawi Aldina! Hekima, thank you for the support, thank you for sometimes being a reason for this work to see light of the day. Thank you for your innocent, yet infectious smiles that often sent me back to my computer to do more work happily even when it seemed impossible. Kgatlhiso, thank you so much Love, one for handsome Hekima and beautiful Hawi, and two for the emotional support. Thank you for being there, thank you for understanding that sometimes I needed to disappear and get some work done. I also cannot sign off without appreciating the love and support from my loving little brother Victor Nduga. As you have always said Victor that I challenge you, from the hindsight, you challenge me more! I love your work ethic, I love your determination to do better, and I am very proud of the young and accomplished lawyer you are becoming. I must say that you challenged me, subtly in many ways and circumstances. I cannot thank you enough, but I know future is there for us to explore. Thank you!

To my academic guide and supervisor Prof Odongo, you are one in a million, you found me at a very vulnerable episode of my life. And through your unmatched wit, you steered me through many academic obstacles, and still insisted on quality. I believe you are a true definition of 'Best or Nothing.' I have learned great lessons from you. I have emulated some of your maverick research approaches and with time and life, I am sure to apply them to thank you appropriately.

While it is impossible to exhaust the list of those who contributed to this journey in one way or the other, I would like to heartily thank the 2016 PhD cohort at Wits Business School, you people provided me with a family several miles away from home, and I hope we maintain the commitment to each other for the rest of our academic journey.

## Dedication

This study is dedicated to my late Father Edward Nduga who, despite my young age believed that I will always be the best in class. I also dedicate this work to my mamma, Alda who has been the greatest pillar of my success. Mamma, I made it!

# CHAPTER ONE

# INTRODUCTION

## 1.1 Background to the study

Determining risk-return trade-offs of financial assets has been a weighty discourse among stakeholders in capital markets. In this regard, factor identification has specifically curved out a special niche within the broader need to understand the drivers of stock price changes. Empirically, financial economists are increasingly searching for practical and robust methods to address the equity premium puzzle and to identify the right factors for asset pricing in different contexts. However, recent developments in the field present hope to researchers as a number of factor identification procedures have recently been proposed in the literature (see e.g., Kelly, Pruitt, and Su, 2019; Pruitt and Su, 2019; and Pukthuanthong, Roll, and Subrahmanyam, 2019). These studies first agree that investment and risk of a portfolio or any financial asset are determined by their systematic risk (factor) exposures (Mora-Valencia, Ñíguez, and Perote, 2017; Pukthuanthong et al., 2018; Ziemba, 1994). Two, they argue that factors are the fundamental yardstick for comparing assets and portfolio performance.

Thus, portfolio characteristics such as volatility and correlation somewhat complicate the search for the true identities of risk drivers in financial asset returns (Pukthuanthong et al., 2019). Anecdotal observation reveals that even well-diversified portfolios are quite volatile. Examples include the main trading indices like the Johannesburg top 40 Index, Johannesburg All-Share Index, Nasdaq, Shanghai Composite, Karachi 100, and Nairobi Securities Exchange 20-Share Index among others. Correlation between the same class of assets in a portfolio is also empirically reported to be relatively higher compared to the correlation between portfolios of different asset classes like stocks and bonds, commodity futures, and metals. High

correlation between assets within class may suggest the presence of a common underlying risk driver on one hand, or presence of multiple common risk drivers on the other hand.

Against this backdrop, the present study is focused on establishing the identity of underlying risk drivers in individual assets and portfolios in developing equity markets. Given the young but evolving financial and economic landscape of the target developing equity markets in this study, describing risk-return behaviour can be challenging. Capital investment in developing equity markets is observed to be associated with substantial risk premiums which in most cases result in high cost of capital (Blin, Ielpo, Lee, and Teiletche, 2018; Caballero, Farhi, and Gourinchas, 2017; Donadelli and Prosperi, 2012). Further, currency fluctuations, capital controls, and economic and political instability are believed to complicate the search for underlying drivers of expected returns in developing equity markets (Erb, Harvey, and Viskanta, 2016).

Other features prominently highlighted include smaller market size, low liquidity or illiquidity, extreme price volatility, trade barriers, weak corporate governance, and lack of well-established legal, political, business and social frameworks that can sufficiently support operations of securities markets (De Groot, Pang, and Swinkels, 2012; Guney, Kallinterakis, and Komba, 2017).

Research on capital market and associated risks in developing equity markets is nonetheless gaining traction. The rise is partly explained by the high, but volatile, returns these markets often offer to investors. Studies document that the attractiveness of these markets is partially driven by the perceived low integration with the world stock markets, which is seen as an opportunity for portfolio diversification (see e.g., Zaremba, Maydybura, Czapkiewicz, and Arnaut, 2019). Hence, the broad objective of this study is to ascertain the salient drivers of variations in equity returns in these markets.

The literature suggests that market-related characteristics invariably influence or persuade individuals to invest in a particular market or security. These include size of the market, volatility of trade, liquidity of the general market and the listed firms, and general macroeconomic conditions (Karolyi and Stulz, 2003). Beyond these market-wide variables, the literature has also identified other drivers of issuer-specific risk sources of risk in stock markets. For example, an increase in size (market capitalization or value of assets) may suggest a reduction in new investment opportunities for the firm and could signal reduced future earnings and cash flows (and by extension, equity returns) (Fama and French 1992). Developing equity markets, however, are hardly characterised by the size phenomenon since the markets and firms trading in them are fairly small but steadily growing at a rate almost comparable to those observed in emerging markets.

For instance, World Economic Outlook (WEO, 2018) indicates that frontier equity markets capitalization to GDP was about 28.6% compared to emerging markets at 66.1%, developed markets at 127.6%, and U.S alone at 165.5%. MSCI report of 2019 revealed that the combined market size of frontier equity markets measured by market capitalization was $146 billion, accounting for about 8.9% growth from their previous year's report. These figures possibly indicate optimism to investors because it presents significant room for growth. However, interested investors still do not have a good idea the sources of risk to look out for in their endeavor to exploit opportunities availed by these markets. This, therefore, is reasonably compelling to warrant an endeavour to identify the underlying dynamics of these markets, and specific risk factors that investors should pay attention to.

However, both Finance researchers and practitioners in developing equity markets unfortunately rely almost exclusively on asset pricing frameworks developed in other markets. But to the credit of a legion of seminal researchers in this domain including Fama and French

(1993), Fama and French (2015), Fama and MacBeth (1973), Chen, Roll, and Ross (1986), Novy-Marx (2013), Acharya and Pedersen (2005) Amihud and Mendelson (1986), Carhart (1997), Ross (1976), and Guo, Zhang, Zhang, and Zhang (2017) among others who have laboured to redefine and refine traditional models, the understanding of risk-returns characteristics in various markets is now made easier. Their efforts have provided a well-defined foundation for new developments in the field, and an opportunity to extend the research to markets with different and evolving dynamics. Their work has also provided clear platforms upon which such studies in less developed markets can be anchored, and their endeavours, though based on the advanced markets features, have generated a great deal of knowledge about the possible identity of factors that explain variations in equity returns in developing markets.

Differences in the identity of risk factors explaining equity returns identified by various asset pricing studies in different settings are believed to arise from certain empirically observed market features such as market segmentation (Azher and Iqbal, 2016; Kodongo and Ojah, 2011), home bias (Maier and Scholz, 2018); non-synchronous trading (Ortiz, Contreras, and Villena, 2015), institutional and infrastructural quality (Stocker, 2016), information efficiency (Kelly, 2014) and accounting quality (Callen, Khan, and Lu, 2013) among others, most of which have been established by Narayan, Narayan, and Thuraisamy (2014) as undesirable and "worse" for developing equity markets relative to developed markets. These features are taken into consideration in this study and are, provided that data allows, empirically evaluated in the process of coming up with a feasible set of factors to describe equity returns in developing equity markets.

Because of these evident differences, classical models have tended not to demonstrate success in describing the risk-return relationship in less developed stock markets as enumerated by Alhashel (2019); Blackburn and Cakici (2017), and Boamah (2017). This relative inability of

standard asset pricing models to fully explain returns in these markets is argued to be caused by the strong assumptions of perfect market conditions underlying asset pricing models and their extensions (Obrimah, Alabi, and Ugo-Harry, 2015). Frontier and developing markets do not manifest features of strong market efficiency which underlie the tests on the classical asset pricing models. Market efficiency is a critical component of asset pricing and price discovery in stock markets. The concept was initially introduced by Fama (1970) and extended in the classical study of De Bondt and Thaler (1985) who examined overreaction of investors to 'unexpected' news. The reaction of the markets to new information is also captured by Shiller (2000) through his irrational exuberance study.

A remarkable number of empirical evaluations shows that classical asset pricing models such as CAPM and its variants, may not hold under certain conditions. For instance, Roll (1977) demonstrates that the single-factor CAPM is rejected when the portfolio used to proxy the market is inefficient. In this regard, the efficiency levels of the market portfolio for developing equity markets are a critical component of the success of these models. Importantly, how soon the markets can incorporate arrival of new information into stock prices, as espoused in irrational exuberance of Shiller (2000) and market overaction of De Bondt and Thaler (1985), is critical for the well-functioning of classical asset pricing models.

Yet, the preponderance of empirical evidence appears to indicate that most developing equity markets are informationally inefficient or only efficient in the weak form. For instance, Jefferis and Smith (2005) diagnoses African stock markets as ephemerally efficient, while Mobarek and Mollah (2016) find time-varying market efficiency in some of emerging equity markets in Africa and Central Europe. Hull and McGroarty (2014) is however categorical that many developing equity markets exhibit time-dependent weak-form market efficiency and become relatively efficient as they develop.

Other than the unresolved efficiency debate, developing equity markets are also characterized by sizable downside risk−the risk of extreme losses due, for example, to excessive volatility of the underlying risk drivers such as exchange rates, commodity prices and general macroeconomic features (Ayub, Shah, and Abbas, 2015). From the macro view of systematic risk drivers, if the macro environment is unstable, the volatility of the underlying fundamentals will have far-reaching effects on the entire market risk and price discovery processes. This is because market participants translate their perceptions of macroeconomic factors into their stock trading behaviours (Pukthuanthong et al., 2019). Estrada (2002) empirically demonstrate that sharp declines in prices occur due to uncertainties surrounding many of the underlying fundamentals. Hence Harvey and Siddique (2000) advocate that skewness is more appropriate in capturing return behaviour and important risk factors in pricing of equities in markets with less developed features because of the uncertainties of their fundamentals which partly propel the small cap stocks phenomenon.

There is further evidence suggesting that security prices in developing and some emerging equity markets exhibit higher degrees of serial correlation which studies attribute to infrequent trading and stale prices observed in most of these markets (see e.g., Rahman, Chowdhury, and Sadique, 2015; and Chowdhury, Rahman, and Sadique, 2017). McKenzie and Faff (2005) find this phenomenon in asset prices to be prevalent when the traded securities are composed of mostly stale prices and low-frequency movement in the asset prices, suggesting that illiquidity of the markets is the main underlying risk driver in such circumstances.

Ngo and Jory (2008), on the other hand, provide evidence illustrating that less developed markets experience strong serial correlation in their stock returns. Their analysis connects serial correlation to information inefficiency and, by extension, stock return predictability. For instance, excess volatility clustering has been documented by authors such as Rompotis (2016)

and Sehgal and Garg (2016) to significantly influence the risk-return relationship in many emerging and developing equity markets. Although, volatility may be good, and forms basis of buying and selling in the stock markets, the fact that volatility clustering makes return predictability possible, especially by chartists who map historical volatility onto expected volatility, makes it a special risk-class for markets where it is prevalent.

Moderate or lack of deep financial sector to fuel the engine of capital-intensive projects in developing equity markets is strongly pointed out by Bekaert and Harvey (2002) to affect stock markets and trading of securities. Lack of well-established debt (bond) markets in developing economies also features prominently as a drawback to investment and development of capital markets in developing countries. In such countries, capital is largely raised through the inadequate banking system which stifles the amount of capital available for both private and public sectors. As argued by Ojah and Kodongo (2015), this may have undesirable consequences on financing of projects that require large capital outlays like building of large physical infrastructures, which are critical to the general wellbeing of the economy.

Various asset pricing theories, such as the intertemporal CAPM of Merton (1973) and the Arbitrage Pricing Theory of Ross (1976), emphasize the role of state variables, implemented by empiricists in the form of aggregate dividend yield, growth rate in industrial production, term spread, bond quality premia, unexpected inflation rate, among others (e.g. Chen, Roll, & Ross, 1986; Park & Sohn, 2016), in explaining the equity risk-return reationship. Such variables are easier to calibrate for well-developed, deeper markets. Hence, implementing the conventional asset pricing models as developed in deeper markets to understand the risk-return relationship in shallower markets where the important building blocks of the theory may not hold may present challenges to reserachers and analysts.

Irrespective of these fundamental incongruities, certain questions still need to be asked when examining what really can motivate an individual to undertake an investment in developing equity markets. Borrowing from the established theoretical knowledge such as rational expectations hypothesis of Muth (1961) and Lucas Jr (1972), one can begin to decipher an explanation. Investors generally use information emanating from the business environment and fundamentals, or information from the financial books of an organization. The latter typically considered include profitability indicators such as return on assets, dividend growth, earnings growth rate, and gearing/leverage ratios among others. Such variables have been modelled in various empirical studies. For example, Fama and French (2015, 2016 and 2017) point to profitability and investment variables as additional natural choices, and indeed, as fundamental firm characteristics capable of influencing investment behaviour in equity markets.

For instance, the size variable, typically proxied by market capitalization, may have important implications for developing equity markets. As already noted, most developing equity markets are characterized by small-cap stocks by developed and emerging markets standards. The small-cap stocks as covered in Fama-French (FF) model tend to produce higher average returns which can be interesting for investors in developing equity markets. On the same scale, growth stocks have over the time outperformed value stocks even though they are considered high risk. A lot of listed companies in developing markets tend to be in the growth stocks category. They do not pay dividends or pay low dividends, are mostly start-ups, high technology-driven and tend to prefer private equity to debt (see, for example, Adjasi, Osei, and Fiawoyife, 2011; Bley and Saad, 2012; Zaremba and Maydybura, 2019)

Now, Fama and French (2015) established that profitability and investment factors struggle to describe risk-return behaviours in portfolios formed of small stocks in their sample. This arguably lends a lot of insight to this study for two reasons; one, these two factors have been

found by numerous empirical studies[1] to have good explanatory power in cross-sections of returns in recent asset pricing literature, two; majority of the firms listed in the developing equity stock markets are generally small in size by developed market standards. The firms are also defined by high growth and inconsistent profitability. It, therefore, remains interesting to ascertain how these two factors, among others, can perform in a large sample of developing equity markets. In the international test of the five-factor model, Fama and French (2017) report the same problems regarding low profitability firms and portfolios formed of low average returns of small stocks.

Taking cues from this knowledge alone, the current study intends to dig deeper into forms of anomalies and common risk drivers of possible relevance in accounting for returns behaviour in developing equity markets. The study strives to identify factors associated with risk premiums and factors that only cause return variations but do not necessarily command risk premiums. These two categories of factors have been the subject of confusion in asset pricing, as factors that command premium are systematic, common, and pervasive, while factors that only move returns present opportunity for arbitrage opportunities to investors (Pukthuanthong et al., 2019). To achieve this, the study considers the prevailing market conditions in developing counties using various recursive methods of identifying these "lucky factors" from a set of candidate factors identified from the "anomalies" literature. The incremental contribution of each factor is determined before deciding on its statistical ability to be a candidate risk factor in a nested model for developing equity markets. That is, the methods applied in this study give each candidate factor a chance so that its specific contribution to the overall asset pricing model is evaluated.

[1] Hou, Xue, and Zhang (2015) report higher Sharpe ratios for investment and profitability factors compared to value, momentum, and size factors, indicating their ability to better describe many of the return anomalies. Kenchington, Wan, and Yüksel (2019) also find evidence of profitability factor in explaining mutual funds return anomalies.

### 1.1.1 Liquidity, Currency, and Commodity Price risks - Fundamental Sources of Risk

Macroeconomic fundamentals have consistently been identified in asset pricing literature as the pervasive drivers of risk in stock markets around the world (Chen et al., 1986; Chen and Chiang, 2016; Pukthuanthong et al., 2019). And there is consensus existing among the mean-variance equilibrium (CAPM) faction of asset pricing literature that a single factor, market beta is insufficient to price all securities in the stock market. The no-arbitrage (APT) faction, in addition, advocates for many pervasive state variables (common drivers) affecting securities returns. They, nonetheless, leave a compelling gap for the exact identity of the pervasive factors informing returns which vary from market to market.

Arising from this gap in knowledge, some empirical studies, such as Chen et al. (1986), have attempted to argue a theoretical justification for including specific macroeconomic variables such as the spread between long and short interest rates, expected and unexpected inflation, industrial production, and the spread between high and low-grade bonds, in the APT. So far, their variables/factors, in addition to some of them being traded, seem to form one of the more complete nested models in the no-arbitrage framework. Other fundamental factors like liquidity, commodity prices and currency fluctuations (risk) are increasingly getting attention of researchers, especially in the less developed markets, as possible significant drivers of risk. However, there is no complete framework in place to adjudicate on a group or set of variables/factors that can jointly describe risk-return relationships especially in developing equity markets.

Focusing on liquidity as a systematic driver of risk; theoretically, it is referred to as the ease of transfer of value and wealth amongst investors at minimal or no cost. As underscored by Chordia, Roll, and Subrahmanyam (2008), liquidity conveys microstructure information indicative of market efficiency. The illiquidity or inefficiency of the developing equity markets

often manifests itself through return autocorrelation, non-synchronicity in returns, and stale prices. Studies such as Bekaert and Harvey (2002) and Marshall, Nguyen, and Visaltanachoti (2015) highlight these characteristics as possible explanations to the differences in returns behaviour between mature markets and developing equity markets. Empirically, Chordia et al. (2008) show that high liquidity is associated with better market efficiency. Further, illiquidity is also shown by Amihud, Hameed, Kang, and Zhang (2015) as an important factor capable of explaining expected returns differentials in developed and developing equity markets.

Liquidity, however, manifests itself in a variety of forms making it difficult to capture in returns. This difficulty has been highlighted by studies as common in markets with data paucity (see for example, Batten and Vo, 2014; French and Taborda, 2018; Lischewski and Voronkova, 2012). Amihud and Mendelson (1986) on their seminal paper on liquidity risk, suggest the use of bid-ask spread: the larger the difference the more illiquid the asset or the market is, and *vice versa*. This approach, however, is extensively debated on the ground of its ability to capture market-wide liquidity, as it is portrayed to only address specific components of liquidity in the market, especially liquidity associated with transaction costs. As for this study, Bid-Ask Spread may provide challenges in the generalization of findings, because the sample of markets under consideration here experience spread caused by reasons, other than the transaction cost, such as infrequent trading, and non-synchronous trading (Hou and Moskowitz, 2005).

Illiquidity or inefficiency  may also arise from the visible hand of governments in controlling the price limits which may end up influencing price discovery mechanisms (Nguyen, Bhatti, and Henry, 2017). Another strand of the literature suggests the use of variables such as order flow imbalance, and volume traded. There has also been the question of whether excess returns can compensate for illiquidity (Amihud, 2002). If this position is true for developing equity

markets, then the relatively higher expected returns realized in these markets could be because of illiquidity being fairly priced in those markets.

Currency fluctuations is a risk factor commonly researched in asset pricing studies. Specifically, developing, and emerging equity market studies have in many instances cited exchange rates risk as highly priced in their returns (see examples such as, Chkili and Nguyen, 2014; Reboredo, Rivera-Castro, and Ugolini, 2016). Asteriou, Masatci, and Pılbeam (2016) report that developing equity markets are characterized by higher exchange rates volatility, which likely constitutes an important source of variability in returns for international portfolio investors. Volatile currency makes international portfolio investors vulnerable to greater uncertainties on their risk-adjusted returns hence they may require higher compensation in terms of higher risk premiums (Kodongo and Ojah, 2014). Thus, inasmuch as these markets, on average, offer higher returns on investment, and therefore attractive for international portfolio diversification, their higher currency risk is a cost that the investors must include in their pricing calculus.

Commodity price is also a frequently cited risk factor receiving considerable attention among researchers and investors in developing equity markets on the ability to influence stock returns. Investing in the commodities market has increased substantially in both developed and less developed markets (Boako and Alagidede, 2016). Differences exist though, for less developed markets, as some commodities, especially natural commodities like oil and minerals, command a significant proportion of export income, hence making these markets vulnerable to the international markets' stability. Commodities markets generally provide an alternative investment vehicle to equity investors as a viable diversification opportunity and an asset class.

The link between commodities and asset prices is nonetheless complex since the effect is both direct and indirect. Changes in commodity prices can be used to gauge future economic

conditions that feed into equity prices of highly commodity-dependent countries (Jordan, Vivian, and Wohar, 2016). For instance, an increase in commodity prices could be a positive signal to the stock market through the expected growth in the economy and the high profitability of commodity-producing firms. Boako and Alagidede (2016) on their part refer to commodities as a significant alternative investment vehicle in Africa, since it lowers risk and increases returns for international investors who prefer to use African equities as an international diversification vehicle.

Most markets in emerging and developing equity markets exhibit high dependence on commodities, thereby any significant change in the price of a leading commodity in the country critically affects the national trade, the main stock index, and the firms whose performance are directly or indirectly influenced by the commodity prices. This, therefore, makes the study of commodity prices in these markets surpass merely the link between commodity prices and equity index performance. If the fluctuations affect trade, then it also affects future cash flows which inform asset valuation. In this case, the prices of the leading commodities become a distinct risk factor that needs to be specifically accounted for in equity prices.

### 1.1.2 Localizing factors in Asset Pricing

As already intimated, global versions of many of the multivariate asset pricing models have been found struggling to comprehensively account for return variations in empirical asset pricing tests. The three-factor model of Fama and French (1993), for example, is shown by Fama and French (2012) in international test as struggling to describe return anomalies in the four regions of North America, Europe, Japan, and the Asia Pacific. However, the local versions of the models do a better job for the countries these authors investigated. Similarly, the five-factor model of Fama and French (2015) when tested on the international portfolio by Fama and French (2017), perform poorly, prompting the authors to resort to local versions of

factors and test portfolios. Guo et al. (2017) use factors and test portfolio constructed of the Chinese market and find significant GRS statistics for most of the return anomalies. Hanauer and Linhart (2015) also find global versions of factor models struggling to capture return patterns of four emerging market regions of Asia, Latin America, Europe, the Middle East, and Africa. Cakici, Fabozzi, and Tan (2013) arrive at the same conclusion for their test of size, value and momentum in 18 emerging stock markets.

The overarching deduction from these studies is that the local factors are well accustomed to the domestic economic environment and characteristics as opposed to global factors, suggesting some form of segmentation of the markets. This being the case, there has been increased attention on some of the local factors' ability to explain the returns in the stock markets or the adaptation of the same firm fundamental factors in explaining regional or local returns.

The significance of local factors is shown by Boamah, Watts, and Loudon (2016) who find that local factors explain more of the variations in returns in an African Index compared to global risk factors. Wen, Lin, Li, and Roca (2015) contend that possible explanation to the inability of the global factors in predicting South African stock prices in the post-1996 could be caused by economic developments, regulatory changes, and information environment in the local economy. Furthermore, developing equity markets are constantly undergoing structural and economic reforms which evidently support the case for local factors having upper hand in explaining equity variations compared to global or international versions of the same factors.

Given these findings, the current study is particularly keen on the impact and effects of local factors in developing a parsimonious asset pricing framework in developing equity markets. This does not imply that the international or global versions of these models are disregarded, the richness of this study lies on the diversity brought about by this mix. Thus, variables

commonly investigated in developing equity markets research such as money supply, capital expenditures, industrial production, GDP growth and volatility, overall market index volatility, firms' cash flows, future dividend pay-outs, term structure, and yield curve twists, Finance Index, Property Index, firms' profitability, long term government bond rates, volume of bank loans among others, form part of significant contenders for the risk factors in this study.

### 1.2 Problem Statement

As has been highlighted in the foregoing sections, the underlying concern for this study lies on the trading frictions that inform risk in developing equity markets. The preceding discussions highlight higher volatility, higher-order autocorrelation, and excess kurtosis as possible explainers of return predictability. Other drivers identified include liquidity risk, currency risk, and commodity price risk. The only fundamental difference with this class of risk drivers is that literature points to them as critically linked to the price discovery processes in many developing equity markets (Loukil, Zayani, and Omri, 2010). Liquidity risk particularly stands out because of the scarce number of investors and securities to trade in developing equity markets (Bekaert and Harvey, 2003; Bekaert, Harvey, Lundblad, and Siegel, 2007). Further, many of the variations reported in returns are as a result of more outstanding country-specific factors such as illiquidity of the entire stock markets (usually represented by an index), high dependence on natural resources (commodities), volatile currencies, volatile returns, unstable macroeconomic environments, and institutional weaknesses such as lack of strict adherence to corporate governance principles (Erb et al., 2016).

Both empirical and theoretical asset pricing research have suggested some explanations to account for differences in the variations in the cross-section of equity returns across markets. Variables such as size (Banz, 1981), leverage, earnings-to-price ratios (Basu, 1983), the book-to-market ratio (Rosenberg, Reid, and Lanstein, 1985), Bhandari (1988)'s leverage or past

returns (Jegadeesh and Titman, 1993) have been found to offer independent information for expected returns across markets. Fama and French (1992) demonstrate that portfolios formed on these characteristics perform better than CAPM in describing cross-sectional variations in expected returns. But is the story replicable in developing equity markets? Existing research in these markets report mixed results, hence, some of the traditional factors could offer important starting point in the quest to identify important drivers of risk in the developing equity markets.

Given the recent interest in developing equity markets among international investors due to their diversification potential, a study that systematically unifies this bourgeoning body of evidence and clearly identifies equity returns determinants in the developing markets is important. Also critical to asset pricing research is the long memory in the returns samples that can accurately let the researcher draw correct inferences regarding the asset pricing factors; however, developing equity markets are characterized by shorter sample periods making asset pricing tests and inferencing more challenging.

For instance, Fama and French (1998) could not conduct an international test of their three-factor model on the developing equity markets due to their relatively short sample period. This shortcoming provides impetus for this study to devise methods and means of judiciously conducting an asset pricing study in the developing equity markets. For example, although uncommon in the literature, the use of weekly observations, rather than monthly observations may be employed on the argument that higher frequency data better reflect ex-ante returns, which asset pricing tests seek to explain, than lower frequency data. However, the use of higher frequency data may also be criticized in the developing markets on the grounds of infrequent trading.

Studies such as Zaremba et al. (2019), Zaremba, Karathanasopoulos, Maydybura, Czapkiewicz, and Bagheri (2018) have provided useful insights on data and asset pricing in

frontier equity markets. Even though the papers appear to address the current asset pricing gap in developing/frontier stock markets, they still leave a compelling gap as they only test the factors/models already in existence to establish which one(s) work better. Zaremba et al. (2019) for instance use existing models to try to explain differences in the cross-section of returns using 167 anomaly portfolios. They use the GRS procedure and find that Carhart (1997) four-factor model modestly price returns in the frontier stock markets.

Our strategy is rather different: while we acknowledge these valuable contributions, we aim to identify factors/variables that actually account for return differentials and actually command risk premium. Rather than asking the model to explain the anomalies, we look for common factors accounting for returns, and factors related to returns but not priced. Note that the second set of factors is crucial for investors as they present arbitrage opportunities. This allows us latitude to include many potential explanatory factors and variables. Our procedure also permits the inclusion of characteristics underlying the factors instead of constructing portfolios that mimic the factors themselves. This gives room for diversity in the identity of the risk factors. It also does not close doors on any factor, characteristic or variable suggested in the literature to have influence on returns.

### 1.3 Study Objectives

a) To identify macroeconomic and firm-specific variables that should be included in a multi-beta asset pricing model for developing equity markets.
b) To test the macroeconomic and firm-specific variables, with a view to establishing a set of factors/variables, that can best capture average returns in developing equity markets.
c) To propose a framework for the pricing of equities in developing countries based on the results in parts a) and b) of this research.

### 1.4 Significance and contribution

The volume of quality scholarly contribution in asset pricing has grown tremendously in recent times. However, there is very little divergence in the literature on the core factors believed to explain asset prices even as empirical researchers continue to churn out anomalies variables, indicating possible asset mispricing (Jacobs and Müller, 2020), but many of which do not appear to withstand rigorous empirical scrutiny (see e.g., Hou, Xue and Zhang, 2020). It is almost standard that Fama and French three- and five- factors models, over and above the original CAPM and APT, have become the vehicles for understanding asset prices as well as portfolio management globally. The building blocks of these empirical models, or the factors are rarely contested (for instance, the five-factor model is built on the well-known dividend discount model framework), but somehow other factors still find a place in describing additional asset return variations. Thus, the new so-called battleground is about the correct identification and measurement of new or additional return factors to reduce the average pricing errors and to improve the explanatory power of asset pricing models. This study makes a contribution to this end by assembling the longest list of possible asset pricing factors and evaluating their potential for accounting for returns differentials in developing equity markets. The triangulation procedures employed are deemed suitable for the type of data and set of countries in the primary focus. That is, we follow a path in which the standard portfolio-based approach is not our primary focus, but complementary to the identification process. Thus, our statistical approaches are geared towards the identification of unique factors in developing equity markets. This does not mean in any way that elegant statistical approaches employed in seminal asset pricing studies such as the GRS procedure in Gibbons, Ross, and Shanken (1989), spanning regressions widely employed in Fama and French-type studies, and the maximum Sharpe ratios employed in Fama and French (2018) and Barillas and Shanken (2018) are inadequate. These procedures are geared towards choosing among nested asset

pricing models following portfolio-based analysis which is different from the focus of this study.

We favour our approach, discussed subsequently, because we are able to determine different classes of factors that are important for investors in our chosen sample of markets. Distinguishing between priced factors and factors only related to return volatility but do not command risk premium is taken as a significant leap in the right direction for asset pricing in developing equity markets. Moreover, relating identified factors to the covariance matrix of returns significantly contribute to the body of knowledge, as the process helps to weed out uncertainties surrounding the ability of the identified factors to influence returns and actually command risk premiums. Furthermore, we are able to deal with issue of spurious factors raised by Harvey and Liu (2021) and Bryzgalova (2015).

Our main contribution to the body literature in asset pricing comes from employing a battery of empirical methods to discover true risk factors associated with stock returns and the factors that command risk premium. Specifically, we consider a comprehensive set of risk factors (financial and macroeconomic, market and non-market, local and global), and use (asymptotic) PCA, Double-LASSO, and Fama and MacBeth (1973) two-pass regressions to identify the pervasive risk factors and their risk premiums. We establish that local market factor, value, momentum, volatility, trade-weighted dollar currency factor, and unexpected inflation factors significantly explain returns variations of frontier equity style portfolios and are priced. Exact identity of risk factors in financial assets remains a significant task for financial economists across the globe. |Consequently, we propose an asset pricing framework for the subject markets

### 1.5 Thesis Outline

This study is structured into six sections (chapters). Chapter 1 introduces the study and provides motivation while outlining the gap on asset pricing in developing equity markets. This chapter

also provides the objectives of the study, problem statement and significance of the study. Chapter 2 outlines theoretical and empirical literature. Chapter 3 presents the empirical methodologies adopted. Chapter 4 describes in detail the empirical methods use for factor identification. Chapter 4 also presents the data, the three samples oof markets used in the study. Chapter 5 extends the empirical work in chapter 4 to test the identify asset pricing factors in an empirical asset pricing exercise. Chapter 6 concludes the study.

# CHAPTER 2

# REVIEW OF ASSET PRICING LITERATURE

## 2.1 Introduction

This section chronicles theoretical and empirical literature on asset pricing. The motivation underpinning this chapter is focused on facilitating the identification of theoretical architecture for a successful and rigorous implementation of an asset pricing framework in markets with imperfect trading environments. The primary objective as elaborated in the preceding chapter is to identify and test risk factors that primarily impact on the wealth positions of investors in developing equity markets. Thus, chapter two is driven by a mantra that to the identification of risk factors should be honed from asset pricing theories. A well-executed analysis of this kind has the potential of yielding new theoretical insights specifically relevant to imperfect equity markets. This development thus must be supported by the implications from the historical implementation of the classical models such as Arbitrage Pricing Theory (APT) and Capital Asset Pricing Model (CAPM). Lessons from empirical literature presented in this analysis disclose the extent to which asset pricing work has transformed, especially on the methodological landscape, and how implementing a study of this nature in less developed markets can be undertaken. The implication of this section is, therefore, to inform the need for this study.

Literature on Asset pricing theory and pricing of risk factors in financial assets has a long and controversial history in Financial Economics. At the inception of what is today known as modern asset pricing theory, Markowitz (1952) played significant role in providing the theoretical foundation upon which many of the classical asset pricing principles are anchored. Markowitz (1952) portfolio selection and mean-variance theories specifically informed theoretical underpinnings for Sharpe (1964), Lintner (1965), and Black (1972) who concluded

that an asset's beta with respect to the market portfolio is an adequate measure for the cross-section of expected returns (the birth of Capital Asset Pricing Model, CAPM). The model's success has thus far been pinned on its parsimony, simplicity, and ability to describe risk-return trade-off by using a single risk factor, the market beta to price financial securities, value companies, aid capital structure decisions, and determine investment decisions in capital markets.

In this review of literature, therefore, the early notion that shaped Capital Asset Pricing Model (CAPM) and its constituent variants are of significant interest. The review also touches on the ensuing limited success of CAPM in both developed and developing equity markets. This strand of discussion paves way for uncovering the underlying characteristics which are then related to the primary objective of this study. As already mentioned, the theory of Portfolio Selection by Harry Markowitz and in addition, the Efficient Market Hypothesis (EMH) of Fama (1970) which describes the activities by investors and how competitive prices of securities are arrived at in the stock market incisively inform the discourse in most of this review. Further, for a complete picture in asset pricing research, the APT model which views systematic risk in returns from the macroeconomic stance is discussed. APT is particularly interesting to this study because CAPM as presented, may not completely address the frictions underpinning the developing equity markets. This is because APT is premised on a set of common pervasive factors that describes the risk-returns relationship in the asset markets.

### 2.2 The theory of Asset pricing

As pointed out in the foregoing, Mean-Variance Portfolio (MVP) and Portfolio Selection theories of (Markowitz, 1952, 1959) naturally becomes the launching pad for theoretical discussion in this study. This is primarily due to the tenets of the two theories which suggest among others that, through diversification, investors can maximize portfolio returns while minimizing the associated variance of their portfolio. Portfolio variance, in this case, is at the

centre of asset pricing because the variance constitutes the quantum of risk in a given portfolio. Investors, however, do not hold one asset over a period or periods and consequently use the covariance or correlation between pairs of assets when determining an optimum diversification strategy. Thus, Mean-Variance theory stresses that an individual security's risk is not of greater concern to an investor, but the security's contribution to the overall variance of the portfolio, measured as the covariance of that security with all other securities constituting the portfolio.

Sharpe (1964), Lintner (1965a), and Black (1972) later wittingly apply these principals to develop Capital Asset Pricing Model (CAPM). The authors' contributions have remained monumental to the theory building in asset pricing precisely because they employed a simple, but intuitive mathematical formula to derive a relationship between risk and returns in capital markets. CAPM algebraically relate excess return of a portfolio to the excess returns of the market to determine risk of a portfolio. The result of this mathematical relationship yields a coefficient or simply beta which quantifies the risk of returns. Empirically, a regression of excess returns of portfolio $j$ on excess returns of market portfolio $m$ produces a regression coefficient $\beta$ as the quantity of risk.

CAPM's empirical appraisal instantly became controversial. Naturally, a group of economists embraced the theory and the assumptions underpinning it, while another group critically questioned the tenability of some of the model's underlying assumptions. This precarious position rendered empirical evaluation of CAPM tendentious from the word go. One of the outstanding controversies has remained to be the use of a single risk factor, the beta to capture all possible risks imbedded in all assets trading in the market. McGoun (1993) argue that the intuition behind the model was well known to investors long before it existed. McGoun critique that CAPM's quantification formula is just an applied mathematical gimmick with no material influence on the relation between earnings and changes in stock prices.

CAPM was also faulted on static and one period basis, where the model restricts investors to single-period investment setup. To counter this limitation, Merton (1973a) introduced Intertemporal version of the model. Merton argues that investors should not only be concerned about their end of period payoffs but must be able to make decision informed by how much to consume and reinvest while considering pertinent factors such as labour income, goods prices, and future investment opportunities over time.

The single factor phenomenon which clouded CAPM's pre-eminence found some sort of redress in a multifactor platform introduced by Ross (1976). Ross (1976) presented an alternative to CAPM capable of accommodating many pervasive risk factors hypothesised to be influencing price fluctuations in the market. This became the birth of Arbitrage Pricing Theory (APT), which asserts that variations in financial asset returns can be attributed to many macroeconomic risk-bearing factors. The new paradigm instantly shifted the debate on general equilibrium asset pricing model from univariate risk factor to multivariate risk factors.

These endeavours nonetheless did not slow the debate and tenability surrounding CAPM. The model remains an active entry point into understanding and conceptualizing financial risk, corporate finance, and cost of capital. Graham and Harvey (2001) conducted a comprehensive survey of 392 CFOs of major corporations and found that over 72% of firms determined their cost of equity capital using the CAPM. This is not surprising because CAPM presents simple but intuitive steps in determining the cost of equity. The theory as already presented is built on the notion of portfolio diversification which places efficiency of the market portfolio at the centre.

Restrictive assumptions associated with CAPM nonetheless remain the key issues of departure between proponents and opponents of the model. In one of the pioneering empirical evaluations, Black (1972) developed a variant of CAPM that ignores restrictive assumptions

such as risk-free borrowing and lending, and short sales of risky assets. Black's version gained traction in many empirical appraisals of the model, only with few adjustments such as introducing of the intertemporal setting by Merton (1973b) to address the unrealistic static position adopted by the founders. Fama and MacBeth (1973) on their part introduced an elegant empirical procedure of testing CAPM. Their innovation remains relevant to date and is almost like a force of nature in empirical asset pricing. Despite many technological developments, new evaluation techniques, and even advancements in statistical and econometric analysis, Fama-MacBeth (FM) procedure still dominate empirical asset pricing tests (Feng, Giglio, and Xiu, 2019; Harvey and Liu, 2021; Pukthuanthong et al., 2018; Sun, 2018).

One of the most outstanding critiques of CAPM to date is arguably the one presented by Roll (1977). Roll successfully questioned tenability of the model given the difficulty in observing the mean-variance portfolio and further argued that testing CAPM is equivalent to testing the mean-variance efficiency of the market portfolio. Roll suggests inclusion of all tradeable assets including those of precious metals, real estate, and anything with tradeable value in order to arrive at the efficient market portfolio. This stand later found support in Fama and French (2004) who extended the list to include human capital and labour returns as possible assets to be traded in the markets. This, however, has not always been the case, hence the real market portfolio continues to be elusive.

Roll's position implies that, for practical and coherent implementation of CAPM, efficiency of the market or the portfolio used to proxy the market must be determined beforehand. This is closely tied to the phenomenon of efficient market hypothesis initially introduced by Fama (1970). Fama (1970) conjecture that all securities in the market reflect all the available and information relevant to their prices. That is, stocks can be classified based on how quickly or efficiently, they incorporate information into their trading prices. These three classifications

include Weak, Semi-Strong, and Strong-Form efficient market hypotheses. In the Weak-form, Fama elucidates those assets associated with this form only reflect historical information in their trading prices. The semi-strong form, on the other hand, reflects both historical information and all publicly available information affecting the asset, while strong form incorporates historical information, publicly available information, and private information.

The overarching objective of Efficient Market Hypothesis (EMH) is that no one can possibly 'beat' the market, and that all securities in the market are efficiently priced, always reflecting relevant and available information about them. EMH, therefore, presents rich platform for price discovery, and has implications for asset pricing. The theory ties with the fundamentals underlying CAPM which argue for uniform expectations and perfect information of the market, in which market is expected to clear off all risky assets. CAPM advocates for investors to hold well-diversified portfolios capable of minimizing variance and maximizing expected returns. Therefore, variance of an individual asset is not of much significance, but the variance of the diversified portfolio is. Individual securities covariance with the portfolio has serious implications for the choices investors make.

*The Case for CAPM*

Given the foregoing discussion, a critical question remains: why would the expected returns on assets differ? To answer this question, we reconsider the building blocks of the CAPM. As is already clear in the preceding discussion, securities included in a portfolio must have different covariances with the portfolio; hence, the pricing of covariance risk is central to the use of the CAPM. But this would require that all investors have instantaneous and costless access to all information regarding markets and securities in all future states of the world. For the most part, perfect information is not available to investors, but for the theory to work, this tenet of the model must be upheld. Fama and French (2004) endeavoured to digest this and prove that the

CAPM is a competent model and that its shortcomings have been because of the difficulties in implementing its valid tests, where researchers often fail to design tests that can adequately measure the risk of the asset relative to a comprehensive market portfolio.

Deducing from the portfolio choice by Markowitz (1959), which provides the foundation for CAPM, it is easy to critically examine the model. In portfolio theory, as in CAPM, the investor's main concern is the expected return of a one-period investment, say at time $t-1$, which produces stochastic returns to be realized in time $t$. Note that, due to the risk-averse nature of most investors, they closely watch the variance of the portfolio, and choose the portfolio that maximizes their average expected returns while minimizing its variance.

Taking the assumption that market participants hold the homogeneous beliefs about the market and that they are perfectly informed, an algebraic relation holds for minimum variance portfolio and can be advanced to prove that all the risky assets in the market are priceable. Assuming that investors hold the same investment, say portfolio $m$, that portfolio would be the most desirable because of being the most diversified, and can be hence taken to represent the market portfolio (and should therefore be efficient). The concern of investors is the variance and covariance of assets to this $m$ portfolio as presented in equation $(1)$. For equation (1) to hold, many assumptions are required to hold. Amongst the many assumptions, three key ones are as follows. First, investors are aware of the distributions of possible returns on all assets/portfolios, which implies perfect information of the market. Second, $m$, which represents all investors' investment choice/decision, is the value-weighted portfolio of all risky assets. Finally, the market is expected to clear all the risky assets if there are risk-free lending and risk-free borrowing opportunities (Jensen, Black, and Scholes, 1972).

Taking a portfolio of a risk-free asset to be $f$, and assuming that there are up to $N$ risky assets to be priced, a simple algebraic relation can be shown as;

$$r_i - \ r_f = \beta_i(r_m - r_f) \quad i = 1 \cdots N \tag{1}$$

The terms can also be rearranged such that $r_i = r_f + \beta_i(r_m - r_f)$ where, $(r_i - r_f)$ is the excess return of an asset $i$, $(r_m - r_f)$ is the excess return of the market (portfolio $m$) and $\beta_i$ is the sensitivity of asset $i$ to the variations in the market portfolio, a measure of systematic risk of asset $i$. Empirically, $\beta_i$ is the slope of a regression relating $r_i$ and $r_m$, and is mathematically represented as $\beta_i = Cov(r_i, r_m)/Var(r_m)$.

The investor's beliefs about the market are summarised in equation (1), $r_i$ is the expected return on asset $i$, $r_f$ is the expected return on the riskless asset, usually proxied by short term government bonds like the Treasury Bills, which by construction, should have zero covariance with the market beta.

Harvey (2001) underscores the importance of the covariance between the asset and the market portfolio to investors. Motivating from portfolio theory of Markowitz (1959), $r_f$ should have a zero covariance with the market portfolio, meaning a zero beta. However, many empirical evaluations of equation (1) have yielded a value different from zero, putting to question the role of risk-free lending and borrowing on the pricing of risky assets. Black (1972) relaxed the restrictive assumption of risk-free lending and borrowing, which structurally changed the model, but concluded that the expected return of any risky asset is still a linear function of its beta. This conclusion underscores the importance of securities' sensitivity to the returns of the market. Essentially, in Black's (1972) explanation, even with or without the restriction of riskless lending and borrowing, investors will still be interested in the variance and covariance risk of their portfolios. For this and other reasons, CAPM has kept its relevance despite its dismal performances in many empirical tests.

## 2.3 Empirical Asset pricing in Developing Equity Markets

In this section, we present a case for why developing equity markets should be treated as a different asset pricing risk class.

Empirical asset pricing in developing equity markets have produced results that fundamentally expose the special risk characteristics in developing markets. For instance, liquidity has been discovered to have better statistical resonance in evaluating risk-return trade-off in developing equity markets compared to developed markets counterparts (Bekaert et al., 2007; Rouwenhorst, 1999). Momentum and Profitability factors have also proved more potent in empirical appraisals of firm fundamental factors in developing and emerging equity markets (Skočir and Lončarski, 2018b; Zaremba, 2018; Zaremba and Szyszka, 2016; Selebogo and Kodongo, 2020). Specific characteristics highlighted in the introductory chapter of this study exposes why there is pronounced effects of momentum and liquidity risk. The chapter shows for example that, in these markets in comparison to their developed counterparts, stale prices, and small firm effects are a common concern. Other notable sources of liquidity premium that literature pronounces to be severe in developing equity markets include exogenous transaction cost, demand pressure, and inventory risk, information asymmetry and search friction (Amihud, Mendelson, and Pedersen, 2006).

One would not help, but notice that, despite the suspicion that institutional variables may be responsible for innovations in the underlying drivers of risk in these markets, research has either chosen to ignore or omit institutional and governance variables in explaining risk-return trade-offs in developing equity markets. Despite their significance on business environment, (Cule and Fulton, 2013), governance indicator variables, have received little attention on their direct impact on securities returns in developing equity markets.

However, more recent studies are nonetheless increasingly incorporating governance indicator variables such as voice and accountability, political stability and absence of violence, government effectiveness, regulatory quality, the rule of law, control of corruption in determining the risk-return relations across markets. For instance, Cao, Qin, and Zhu (2019) establish that local corruption leads to stock price crash in China. Ahmed (2020) uses system GMM to explore the impact of corruption on equity market performance on a broad sample of Islamic and conventional equity markets in emerging and developed markets. Their results show that corruption exerts significant negative effects on conventional and Islamic stock returns alike. Ahmed (2020) further exposes that, conventional and Islamic emerging countries markets are more sensitive to corruption than developed countries stock markets.

Sherif and Chen (2019) investigate the impact of governance quality variables; accountability, level of corruption, and governance effectiveness on momentum premiums in the international setting and establish that quality of governance consistently affects international momentum profits. Nguyen, Nguyen, and Schinckus (2019) similarly employ system GMM to investigate the impact of institutional environment, government effectiveness, regulatory quality, rule of law, and control of corruption and produce evidence suggesting significant positive impact of the variables on stock return co-movements between a selected emerging and US stock markets.

### 2.4 Arbitrage Pricing Theory (APT)

The APT model forms a significant theoretical basis upon which risks associated with financial assets can be modelled. Ross (1976) presents a linear $k$ −factor return-generating process of the form:

$$\tilde{r}_i = E_i + b_{i1}\tilde{f}_1 + \cdots + b_{ik}\tilde{f}_k + u_i \quad i = 1, \cdots, n \tag{2}$$

where $E_i$ the expected return of asset $i$, $\tilde{r}_i$ is $n$-dimensional vector of random return of asset $i$. $\tilde{f}$ is the vector of common factors ($\tilde{f} = 1, \cdots, k$) postulated to influence returns of all the assets in the market with up to $k$ common factors. $b_{ik}$ measures the sensitivity of returns to the movement in common factors $\tilde{f}_k$. The last term in the equation, $u_i$ is the unsystematic component which is only idiosyncratic to the $i^{th}$ asset. In empirical estimations, the idiosyncratic term should be normally distributed with mean zero, $E(u|f_j) = 0$, and constant variance, $\sigma_u$.

Considering the algebraic relations depicted in equation (2), it is evident that APT shares the zero-beta asset portfolio assumption with the CAPM. And similar to CAPM, the zero-beta asset in APT is proxied by the one-month Treasury bill which is postulated to have zero covariance with the other common risk factors. The expected return of an asset under the APT can be expressed as a linear combination of the factor sensitivities and the factor weights, where factor weights take the form $\lambda_0, \lambda_1, \cdots, \lambda_k$, such that

$$E_i = \lambda_0 + \lambda_1 b_{i1} + \cdots + \lambda_k b_{ik} \text{ , for all } i \qquad (3)$$

This being the case, then one of the difficulties faced by empirical asset pricing researchers is to identify the pervasive factors, $f_k$, in order to estimate equation (3).

### 2.4.1 Empirical Evidence of APT in Developing Equity markets

Classical asset pricing literature conjecture that only a small number of pervasive state variable can fully describe cross-sectional variation in stock returns (Breeden, 1979, 2005; Lucas Jr, 1978; Rubinstein, 1976). Ross (1976)'s proposition is anchored on the no-arbitrage principle which that suggests few macroeconomic variables would suffice to significantly explain the variations in stock returns.

The Arbitrage theory, just like CAPM has attracted numerous empirical tests. Several tests agree with Ross's hypothesis concluding that there are indeed more than one state variables responsible for return variations (see Chen, 1983); and Roll and Ross, 1980) particulalrly in the deevloped equity markets where the bulk of the tests have been done. However, even within the developed markets circles, most of the debate on Ross's hypothesis has been about the identity of the pervasive macro factors. The APT advocates for $k$ return generating pervasive state variables whose clear identities are not provided by the theory. Therefore, the main purpose of the present study is to use a clear, coherent, and tractable factor identification strategy to try to identify the perversive macroeconomic factors in the developing equity markets. In the early literature, factor analysis procedures were preferred to gather the state variables (Bilson, Brailsford, and Hooper, 2001). Like many procedures, factor analysis is not without its strengths and shortcomings. For instance, researchers such as Fung and Hsieh (2004) and Kelly and Pruitt (2015), who support the procedure, argue that it offers several macroeconomic variables a chance to be included in a pricing equation as reduced principal components. Others such as Dhrymes, Friend, and Gultekin (1984) note that the procedure is not accurate, specifically pointing out that its application in Roll and Ross (1980) is not stable given that the number of factors determined increase with the number of securities analysed.

This study, however, is of a strong belief that combining theoretical propositions of APT with practical situations in developing countries stock markets can help to identify factors potentially important for securities pricing in this study. The review below is, therefore, centred around the possible identity of the factors postulated in the developing market literature to have a direct bearing on the firm's financial performances and stock prices. One of the early studies to try to identify a possible set of factors for the APT is Chen et al. (1986), who argue that their set of factors account for major variations in the economy and have the ability to influence expected cash flows and general performance of firms in the economy. In the spirit of Chen et

al. (1986), Nijam, Ismail, and Musthafa (2018) investigate macroeconomic determinants of stock market returns in Sri Lanka using exchange rates, goods prices, interest rates, production index, market stress index, money supply, dividend yield, liquidity, and volatility of the stock market. Their results indicate that the industrial production index, interest rate, and exchange rates positively and significantly influence stock returns of Colombo Stock Market, while variables such as inflation (goods prices) have a negative impact on stock returns.

The preponderance of the evidence model stock prices in less developed equity markets using both local and international macroeconomic variables. For instance, Chen and Chiang (2016) use a battery of local and international US-based factors and find strong evidence that the factors are priced into the Chinese stock market at varying strengths. The authors establish that the US measure of market distress is strongly and significantly priced both at the sectorial level and national aggregate level.

Chiang and Chen (2016) also find evidence linking the Taiwanese stock market to a number of global and local factors. This study among many have given clear evidence that the investment environment in most emerging and developing markets can easily be predicted by the movements in major international stock market events, for instance both Nijam et al. (2018) and Chiang and Chen (2016) use a global factor proxied by S&P 500 index and establish strong statistical evidence that the variable is significantly priced in the returns of the two markets investigated. They also show that the distress measure of US market is negatively priced in the stocks of the two tested markets, indicating cointegrating movements, or close covariance of the US markets and the markets

Dimic, Orlov, and Piljak (2015) investigate the effects of macroeconomic factors in stock returns for developed, emerging, and frontier markets. Using political stability as one of the macro variables, the authors find that the variable manifests itself on prices through the

government actions, and that political stability variable is an important factor influencing frontier markets stock returns. On the other hand, Dimic, Kiviaho, Piljak, and Äijö (2016) find that political stability and the stability of the macroeconomic environment are both important for influencing stock price movements in the frontier markets. Using wavelet analysis approach, Dimic et al. (2016) find that monetary policy affects returns in the short horizon, while inflation and stock market volatility affect returns in the long run.

The varying empirical evidence from this strand of literature may suggest something peculiar about the characteristics underlying the price discovery process in markets with less developed features. Information efficiency and level of integration with other markets are offered as a plausible explanation to such irregularities. For instance, Neaime (2015) reports that Frontier markets are slow in responding to general market information regarding the trading news.

Some empirics conjecture that, even with weaker market characteristics and higher returns, investors in developing equity markets are mostly concerned about the ability to convert their investments quickly and efficiently into cash and cash equivalents with limited loss (Marshall et al., 2015). In the absence of this, liquidity will have the ability to attract a significant premium. This, therefore, makes liquidity or illiquidity a possible tradable risk factor in the stock returns of developing equity markets (Graham, Emid, and Feather, 2013; Speidell and Krohne, 2007).

A number of authors have reported the impact of liquidity on returns; however, there is still a contention regarding methods of capturing its effects across the markets studied (see Chordia, Roll, and Subrahmanyam, 2002; Amihud, 2002;, and Pástor and Stambaugh, 2003). This could be because liquidity as a concept, has two subconstructs, one being the ability to transfer value with limited loss, the second being ability to *quickly* transfer value with limited loss (Gabrielsen, Marzo, and Zagaglia, 2011). And as Chordia, Roll, and Subrahmanyam (2001)

and Jones (2002) submit, liquidity remains the secure link between demand and supply sides of the market.

Capturing these constructs of liquidity in frontier-developing equity markets can be challenging given the trading frictions alluded to earlier in this study. Because of the significant time delay in getting the right value of financial security, sellers of financial securities are inclined to demand compensation through higher returns on the securities (Lesmond, 2005). Buyers too are persuaded to demand a significant discount in that specific financial asset because of the uncertainty regarding future security sales (Amihud, Hameed, Kang, and Zhang, 2015b). The markets under investigation in this study are associated with significant transaction costs due to illiquidity (De Groot et al., 2012; Marshall et al., 2015), making it an interesting factor.

### 2.4.2 Selected Macroeconomic variables under consideration in the study

Theoretically, the general prices of goods and services can impact the levels of investment in financial securities. In periods of high prices, consumers hedge the high price effects by buying investment positions in financial assets (Tiwari, Dar, Bhanja, Arouri, and Teulon, 2015). Rising prices of goods, therefore, make financial assets attractive, causing their prices to increase and expected returns to fall. As the supply and demand forces play out, investors form expectations and adjust their utility functions of the future expenditure given the present circumstance. Because the economy normally has its cycles, prices are bound to start falling as investors revise their expectations. Investors will, therefore, look for financial assets that can do better in bad times to counter the effects of excess inflation or hyperinflation periods. If this scenario turns out, then does inflation practically offer hedging opportunities to investors in financial assets? This might look like the famous egg-hen analogy, but the variable is of significant consequences to investments in financial assets.

Interest rates is another macro variable that may have an impact on the prices of securities. Indeed, studies conjecture that interest rates and stock prices have a causal relationship, a relationship responsible for core decisions in investment such as asset allocation, risk management, portfolio diversification and asset pricing (Jammazi, Ferrer, Jareño, and Hammoudeh, 2017). Interest rates affect the cost of equity through many channels: it has a direct effect on discount rates used in equity valuation and affects the cost of capital which has an impact on the present value of future cash flow from capital investments. Interest rates also affect bond prices because of the inverse relationship between them. Coupon paying bonds ideally must pay the operating interest rate as coupon to investors, which remain constant for the life of the bond: if interest rates surge upwards, the value of this bond goes down because it cannot pay the high rates available in the market (Lettau and Wachter, 2011).

Therefore, high interest rates environment is not conducive for large capital projects. For stocks, since high interest rates correspond to higher discount rates, this results in high risk, high unstable returns, and low prices of securities. In fact, this is typical of less developed economies, they usually offer high interest rates, partly to attract foreign direct investments and investments in their bonds markets (Piljak and Swinkels, 2017). Jammazi et al. (2017) also report that interest rates affect portfolio rebalancing by investors because as return on bonds go down, stocks become attractive, and investors prefer to include stocks in their portfolio as they offload fixed-income securities. It is also true that when interest rates are high, investment in the stock market goes down because it is expensive to raise funds to invest in stocks (Lettau and Wachter, 2011). For heavily geared firms, high or increasing interest rates pose serious threats to their revenues and hence cash flows as the firms have to part with a substantial portion of their revenues in paying off debt. This results in low net profits affecting return on equity and earnings per share.

Economic theory also postulates that high interest rates lead to crowding out of private sector, and only government and large corporations are able to afford the high cost of funds. For productivity, this is counter-effective because companies face a high cost of funding productive projects (Alesina et al., 2015). In the process, the general economy slows down. A slowing economy corresponds to declining prices of stocks (Kiviaho, Nikkinen, Piljak, and Rothovius, 2014; Otieno, Ngugi, and Muriu, 2019). If these major macroeconomic components are not stable, future expected cash flows become unpredictable (Asgharian, Christiansen, and Hou, 2015). This unpredictability may cause investors to revise their expectations and utility-maximizing functions. Chen et al. (1986) argues that only factors with ability to alter expected cash flows can enter equity pricing calculus. For interest rates, Bilson et al. (2001) note that it is not interest rates that matter, but their effects on the yield curve.

Amihud and Mendelson (1986a) looks at liquidity and affirm that liquidity bears risk in the financial markets. Jones (2002) notes that aggregate liquidity contains cyclical components for US stocks and their measure of liquidity qualifies the variable to be used as a macroeconomic factor. Empirical literature conjecture that developing and emerging equity markets suffer from severe to chronic illiquidity, and that most of the proxies used in the developed and advanced markets may not adequately capture its effects on the returns (Marshall et al., 2013). Liquidity is a significant cost that investors consider and price in their risk pricing calculus (Jun, Marathe, and Shawky, 2003; Lesmond, 2005; Smith and Dyakova, 2014). In their analysis of the liquidity effects on stock prices, Marshall et al. (2013) catalogue 14 proxies of liquidity in frontier stock markets. The authors' metrics range from estimates of spread to price impact measures. This study will adopt a mix of Amihud (2002) and Amihud, Mendelson, and Lauterbach (1997) that make use of aggregates volume and stock index as a measure of liquidity at the aggregate level, hence qualifying as a macro component. Almost all studies that

have investigated the effect of liquidity in emerging and frontier stock markets find Amihud (2002)'s measure to be the most appropriate.

In developing equity markets, commodity prices may also command significant risk premiums capable of altering cash flow expectations, and studies have found the influence of changes in commodities prices on returns of equities (Raza, Shahzad, Tiwari, and Shahbaz, 2016). Theoretically, rising commodity prices especially those used in the production process, signify the rising cost of production and hence negative effects on future cash flows. This expectedly should hamper aggregate investment set as firms report lower profits and even losses. For countries that heavily rely on commodity exports, variations in commodity prices easily permeate into the economy through reduced revenues. Evidence suggests that most African stock markets commove with commodity prices: for instance, Dutta, Nikkinen, and Rothovius (2017) find that jumps in oil prices cause uncertainty in equity prices in the Middle East and some selected African stock markets.

Kodongo and Ojah (2011) and Kodongo and Ojah (2014) provide evidence on exchange rates effects on African Stock Markets returns, documenting that exchange rate risk is conditionally priced (Kodongo and Ojah, 2014). This finding is important for the present study; however, exchange rates is not tested as one of the common factors commanding hedging concern in the frontier stock markets. Since commodity prices that form part of the regressor variables are valued in US dollars, the effects of currency fluctuations may be implicit in the model.

Money supply is also considered important as a macroeconomic risk-bearing factor in the stock markets, especially in economies where monetary policy may not be potent enough to affect international prices, or a country's exposure to international price fluctuations (Bahloul, Mroua, and Naifar, 2017). Changes in money supply have effects on the equilibrium position of money in the economy, which may alter the purchasing power of the investors (Bilson et al.,

2001). Thanh, Canh, and Maiti (2020), document that changes in money supply (monetary policy shocks) have a significant lagged impact on stock prices in India. Evaluating monetary policy landscape under Taylor rule, Thanh et al. (2020) establish that monetary policy shocks significantly influence Indian stock returns for the period between 1994 and 2018. Jiang (2018), using a Markov-switching dynamic factor model, provide evidence indicating that changes in monetary policy regimes and stock market conditions have significant influence on the relationship money supply and stock returns. While tracing specific monetary policy events by the Brazilian Central Bank, Val, Klotzle, Pinto, and Barbedo (2018) find that, although significant, changes in money supply on influence a small part of the variation in the stock market.

It has been shown that developing markets offer good returns to investors and are invariably considered as destination for international portfolio risk diversifications. There is research evidence that diversification of investment opportunities once offered by emerging stock markets to global portfolio investors are fast fading, (see (Christoffersen, Errunza, Jacobs, and Jin, 2014; Christoffersen, Errunza, Jacobs, and Langlois, 2012)) thus creating the opportunity for developing equity markets as plausible alternatives for portfolio risk diversification.

### 2.5 Selected empirical nuances in Asset Pricing

Modern empirical asset pricing debate is largely driven by nuances in econometric and statistical applications. For instance, continued discovery of risk factors has resulted in high-dimensional space in asset pricing occasioning the curse of dimensionality. Arguably the curse of dimensionality has considerable impact on tractability of the majority of factor models. In response authors have devised various state-of-the-art-empirical strategies to counter the curse of dimensionality. A lot of this development is arguably supported by technological development now available through big data analytics. On the theory side, however, the two competing frameworks of CAPM and APT continue to be the cornerstone of asset pricing, with

much attention now directed to the optimal procedures for arriving at the real risk drivers to span the models. Harvey and Liu (2021) deploy a method based on bootstrap technology to extract a set of non-spurious, tractable, and parsimonious risk drivers. Their procedure reduces the dimensionality space of important risk factors, simultaneously taking cross-sectional dependency into account. They aver that the methodology can be expanded to include any asset pricing model. They use the Fama and MacBeth (1973) procedure to evaluate the risk price of the factors identified through their bootstrapping technology.

Kelly et al. (2019) and Kelly, Pruitt, and Su (2017) employ another elegant statistical procedure to select among important risk factors in the universe of asset pricing factors. Their method dubbed Instrumental Principal Components Analysis (IPCA) allows them to comb through 36 firm characteristics. IPCA is motivated from the instrumental variable procedure commonly used in classical econometric methods like the Generalised Method of Moments (GMM). They combine it with the classical dimensional reduction technique of Principal Components Analysis (PCA). Kelly et al. (2020) note that their method differs from the conventional PCA or factor analysis because of the ability to consistently recover the identity of the factors or variables in the system. Kelly et al. (2019) argues for using characteristics in their factor identification procedure as opposed to constructed portfolios. Their results reveal that 5 factors (characteristics) outperform all the factor-based models, especially the CAPM and Fama-French factors.

Freyberger, Neuhierl, and Weber (2017) also conduct an asset pricing test using 36 commonly tested firm characteristics. They too oppose the use of portfolio sorts on characteristics arguing for independent risk drivers to avoid "curse of dimensionality" associated with portfolio sorts. They use Group LASSO (Least Absolute Shrinkage and Selection Operator) which provides two important solutions to the asset pricing problem: *a)* model selection and *ii)* nonparametric

estimation. Model selection has the ability to determine the incremental predictive power of each characteristic, while nonparametric estimation does not impose strict distributional requirements on the data. Freyberger et al. (2017) establishes that only 15 from a large list of 67 characteristics have independent explanatory power for expected returns.

Pukthuanthong et al. (2019) on the other hand, motivate their asset pricing procedure from a position not so radical to portfolios sorted on characteristics but with ability to arrive at genuine risk factors. They specify the conditions that a genuine factor must satisfy. Accordingly, a genuine risk factor *"must be related to the covariance matrix of returns, must be priced in the cross-section of returns, and should yield a reward-to-risk ratio that is reasonable enough to be consistent with risk pricing."* They, therefore, employ a battery of procedures through what they fame as a "protocol". To determine the covariance matrix of returns, their protocol uses the Asymptotic Principal Components Analysis (ACPA) procedure of Connor and Korajczyk (1988b). To achieve the desired relationship between candidate risk factors and the covariance matrix of returns, Pukthuanthong et al. (2019) employ Canonical Correlation Analysis (CCA) [2]of Hotelling (1936) to select among many factors suggested in asset pricing literature. CCA reduces the dimensions of both the dependent variables and independent variables while simultaneously maximising their linear relationships. From a list of 15 variables proposed in the literature, the authors identify 8 potential risk drivers.

Feng et al. (2020) also present another nuanced factor identification procedure to comb through a universe of suspected underlying risk factors in financial markets. Feng et al. (2020) argue that their methodology is able to determine the incremental value of any suspected asset pricing factor. However, despite the robustness of procedure, their premise might prove contentious.

[2] CCA describe the relationships between two sets of variables, in this case the reduced form asset returns, and the candidate risk factors. The procedure is aimed at arriving at the maximum linear combination between the two sets of variables.

They introduce two sets of factors, where one is deemed trustworthy priced factors such as size, value, and momentum, while the other is suspected to only provide some description of the cross-section of returns but might be weakly correlated to the underlying drivers of volatility. Giving a justification that the latter set of factors might produce weak linear combinations with stock returns, they may be strongly correlated to the former group, hence ignoring them is tantamount to omitted variable bias. Consequently, they employ Double-Selection LASSO together with Fama-Macbeth regression technique to choose factors and test their risk premiums.

By no means the literature surveys highlighted here can be declared complete, or to have exhaustively reviewed all the competing factor choice paradigms.

### 2.6 Emerging knowledge gap

The research objectives proposed in this study deviate from the studies of this type in many ways. In addition to testing existing theories and common asset pricing variables (factors) which many studies attempt to do especially in the type of sample in this space, the study aims at providing a new asset pricing framework for developing equity markets. With it, a new set of factors have been diligently identified through statistically tractable triangulation process, where competent empirical procedures in the literature are put to test, and the resulting factors must then be trusted to be the right drivers of risk in developing equity market returns. This in itself aid in advancing knowledge of asset pricing. The triangulation approach employed makes use of Asymptotic Principal Components Analysis (APCA), Canonical Correlations Analysis (CCA), Double Selection Least Absolute Shrinkage and Selection Operator (DS-LASSO), Fama and MacBeth two-step regression, and Generalised Method of Moments (GMM).

Instead of only relying on portfolios, the study also attempts to implement individual firm returns to uncover their common underlying drivers. This is specifically done at the point of

determining significant covariance matrix of returns through principal components analysis. International tests of asset pricing have revealed some interesting outcomes, and the performance of international factors such as international beta as opposed to local beta have shifted the attention of researchers to local beta, which has in many instances produced statistically stronger parameter estimates. This, in turn has elicited numerous empirical questions about stock market integration and the use of local vs global pricing models. The pricing of local factors could have far-reaching ramifications in terms of risk prices and the demand for higher premiums by both local investors and international investors alike. To account for this point of departure in literature, study assembles a large number of domestic and global macroeconomic factors to test their ability to price risk in developing equity markets. Furthermore, a comprehensive comparative analysis is conducted, where similar tests conducted for developing equity markets are also performed for emerging and developed equity markets.

# CHAPTER 3

# THEORETICAL AND EMPIRICAL ASSET PRICING FRAMEWORKS

## 3.1 Introduction

The fundamental purpose of this study is to systematically develop an asset pricing framework that fits capital market dynamics in developing equity markets. The study is built upon dynamic multifactor asset pricing models located within the two major competing approaches to asset pricing frameworks of Capital Asset Pricing Model (CAPM) and Arbitrage Pricing Theory (APT). Studies such as Pukthuanthong et al. (2019), Barillas and Shanken (2018) and Sun (2018) have put forward strong cases for multifactor asset pricing models that employ both firm characteristic variables and pervasive exogenous systematic macroeconomic variables.

The literature section has demonstrated that the standard mean-variance asset pricing model (CAPM) in its original status with strong assumptions, does not present a strong case for describing risk and returns in markets with significant trading frictions. Further, the literature review documents numerous extensions to the CAPM model that still leave a compelling gap in describing returns in markets with trading frictions. For instance, Zaremba and Umutlu (2018) affirmed that the size phenomenon records weak performance because of the dominance of small capitalization stocks even at the industry levels of small markets.

It is also worthwhile stating that most of the extensions on firm characteristics factors are also plagued by the efficiency of both the firms and the markets in which the securities trade. Studies that extend asset pricing tests using variables/factors sorted analogous to those of deep markets sorting criteria have become under scrutiny, and the literature has begun to question their ability to completely account for return variations and command significant risk premium. Of these extensions, notable exceptions exist, these include momentum, profitability, and liquidity

factors. Nonetheless, most firm fundamental factors heavily rely on the mean-variance efficiency of the portfolio (Vo and Truong, 2018).

Fama and French (2004) in defence of the perceived failure of CAPM caution researchers about methodological bias. Specifically, they argue that many researchers have been unable to appropriately construct and measure the underlying portfolios. Fama and French's point of view had been earlier captured by the critique of Roll (1977) who also pronounced that the shortcomings of the model are purely a consequence of inability to identify the most efficient and comprehensive market portfolio[3]. The empirical challenge often faced is to find this efficient market portfolio that has all possible tradeable assets such as stocks, bonds, human capital, real estate and many more. Testing this portfolio is equivalent to testing market efficiency.

It has also been indicated here that CAPM and its variants perform well when the most efficient portfolio is used to mimic the entire market return and systematic risk. On the other hand, the fact that CAPM relies on the assumption of strong market efficiency, which rarely holds in practice, risk variables that explain the portion of equity returns not captured by the original CAPM have been identified in several formats. As a result, this continuously crystalizes to methodological efficiency and astuteness. The fact that many of the discovered asset pricing factors have been a result of methodological approaches present a rich ground for a better methodology to be used to ascertain or discover true factors in the financial asset returns. In this study, tests rely on pervasive macroeconomic risk factors, firm characteristics factors, and test portfolios that mimic factors.

[3] Fama and French (2004) discourse that a comprehensive portfolio is not only limited to financial assets traded in a securities market, but may also include consumer durables, real estates, and human capitals.

### 3.2 Population and Sample

To identify developing equity markets, we use the classification criteria proposed by the United Nations World Economic Situation and Prospectus (WESP), which classifies countries as developed economies, economies in transition, and developing economies (WESP, 2017). Countries are chosen from these broad categories based on data availability. This is because of some of the features highlighted in the first chapter of this study such as non-trading, lack of consistency in statistical databases, the collapse of stock exchanges due to political and economic instabilities, persistent delisting of firms, among many others. For these and other reasons, the study supplements the list by relying on the Morgan Stanley Capital International (MSCI) database to identify countries with equity price data for the period of study. Even though the focus is on the developing equity markets, the sample also includes some emerging and developed equity markets for robustness checks. In the empirical implementation of the chosen or identified risk factors, these different classifications become instrumental in testing the validity of the identified risk factors across the markets. The data are sourced from Bloomberg and DataStream databases. In some circumstances, national stock markets are contacted for verification of the data. This is due to potential inconsistencies in reporting and capturing of data by the two main databases used. Table **1** shows the markets that have been sampled for this study.

The study covers the period between January 1996 and February 2020. This period is not consistent for all the countries as some do not have the data for the entire period. This period is chosen on the basis of having witnessed a number of stock market infrastructural developments and availability of trading data, especially in the African Equity markets (Rossouw, 2005). Globally, the period covers the stock market boom preceding the Global Financial Crisis (GFC) of 2007-2009 and the decline period, giving both the pre- and post-crisis developments. Although the focus is not much on the events of the GFC, the aftereffects

of the crisis led to significant structural and institutional readjustments in many equity markets (Stark, 2009). The study tests this effect in the data by separating the sample into two (1996 to 2009, and 2010 to 2020). The choice of the countries is also targeted at testing if there have been any improvements on market integration. Developing markets have often been characterized by low or negative correlation with the rest of the global markets (Economou, Gavriilidis, Kallinterakis, and Yordanov, 2015; Labidi, Rahman, Hedström, Uddin, and Bekiros, 2018; Marshall et al., 2015).

For instance, World trade statistics[4] indicate (International Trade Organization) that GFC period seems to have been the boom period for most of the stock markets in Africa which also served to illustrate a point on the integration of the African (developing) equity markets and the world equity market (Sugimoto, Matsuki, and Yoshida, 2014). However, the calm period following the end of the crisis witnessed much volatility in the developing equity markets due to capital flight back to the developed markets (Maghyereh, Awartani, and Al Hilu, 2015).

**Table 1: Sampled Stock Markets**

| Country | First Observation | Last observation |
|---|---|---|
| Developing Countries | | |
| Argentina | 1996/01/02 | 2020/02/01 |
| Bahrain | 1997/04/16 | 2020/02/01 |
| Bangladesh | 2009/03/02 | 2020/02/01 |
| Croatia | 1998/06/30 | 2020/02/01 |
| Jordan | 1997/10/16 | 2020/02/01 |
| Kazakhstan | 2004/05/21 | 2020/02/01 |
| Kenya | 1996/01/02 | 2020/02/01 |
| Kuwait | 1996/02/14 | 2020/02/01 |
| Lithuania | 1997/06/13 | 2020/02/01 |
| Mauritius | 2008/11/24 | 2020/02/01 |
| Morocco | 1997/01/02 | 2020/02/01 |
| Nigeria | 2001/01/03 | 2020/02/01 |
| Oman | 1996/01/02 | 2020/02/01 |
| Pakistan | 1997/03/05 | 2020/02/01 |
| Romania | 1997/10/02 | 2020/02/01 |
| Serbia | 2005/04/04 | 2020/02/01 |
| Slovenia | 1998/07/01 | 2020/02/01 |

[4] The statistics is available on the WTO Staff Working Paper ERSD-2013-01 by Auboin and Engemann (2012).

| | | |
|---|---|---|
| Sri Lanka | 2002/02/03 | 2020/02/01 |
| Tunisia | 1999/03/11 | 2020/02/01 |
| Vietnam | 2001/03/12 | 2020/02/01 |
| Emerging Markets | | |
| Brazil | 1996/01/02 | 2020/02/01 |
| Chile | 1996/01/02 | 2020/02/01 |
| China | 1996/01/02 | 2020/02/01 |
| Egypt | 1996/01/02 | 2020/02/01 |
| India | 1996/01/02 | 2020/02/01 |
| Indonesia | 1996/01/02 | 2020/02/01 |
| Malaysia | 1996/01/02 | 2020/02/01 |
| Mexico | 1996/01/02 | 2020/02/01 |
| Peru | 1996/01/02 | 2020/02/01 |
| Poland | 1996/01/02 | 2020/02/01 |
| South Africa | 1996/01/02 | 2020/02/01 |
| Thailand | 1996/01/02 | 2020/02/01 |
| Turkey | 1996/01/02 | 2020/02/01 |
| Developed Markets | | |
| Australia | 1996/01/02 | 2020/02/01 |
| Austria | 1996/01/02 | 2020/02/01 |
| Belgium | 1996/01/02 | 2020/02/01 |
| Finland | 1996/01/02 | 2020/02/01 |
| France | 1996/01/02 | 2020/02/01 |
| Norway | 1996/01/02 | 2020/02/01 |
| Portugal | 1996/01/02 | 2020/02/01 |
| Singapore | 1996/01/02 | 2020/02/01 |
| Spain | 1996/01/02 | 2020/02/01 |

Table 1 presents the countries included in this study. There are 20 developing equity market countries, 13 emerging and 9 developed equity markets

### 3.3Theoretical Asset Pricing strategies

Theory of asset pricing conjecture that there exists a linear combination of the covariance matrix of risky assets and certain risk factors in the stock markets. Capital Asset Pricing Model (CAPM) of Sharpe (1964), Lintner (1966) and Black (1972), and Arbitrage Pricing Theory (APT) of Ross (1976) provide theoretical foundations for this relationship. CAPM predicts that market beta describes returns of all risky assets in the market while the APT postulates existence of more than one pervasive risk factor influencing financial asset returns. Both the models are predicated on the principle that investors are compensated in the marketplace for bearing systematic risk. Because different assets yield different rates of returns, and returns vary across securities, the goal of any asset pricing test is to produce the identity of the factors

responsible for return volatility and associated risk premium (Kelly et al., 2019; Kozak, Nagel, and Santosh, 2018; Lewellen, 2014).

Given the "zoo of factors" in asset pricing literature as pronounced by Feng, Giglio, and Xiu (2020), one would need to tread carefully in determining the real priced risk factors in stock returns. For example, Harvey et al. (2016) identifies 316 factors in published finance literature and propose a restrictive procedure of allowing new factors into the asset pricing equation. Harvey et al. (2016) further notes that the rate of discovery of new factors has since slowed down due to the amount of work already undertaken in asset pricing. They use frequentist technique to comb through the 316 factors and argue that their restrictive summary statistical hurdle of $t-$statistic equal to 3 or above should be implemented by researchers for a factor considered relevant in pricing equity returns.

On the other hand, Green, Hand, and Zhang (2013) document about 330 return predictive signals of which they test 94 in Green, Hand, and Zhang (2017) using Fama-MacBeth regressions and find only 12 of them providing reliable information about US monthly stock returns. Lewellen (2014) test 15 return predictors using rolling Fama-MacBeth regressions as well but do not provide a selection criterion for factor selection. McLean and Pontiff (2016) investigate out-of-sample return predictability of 97 variables to determine their consistency in the post publication and found significant reduction in the predictability of the variables in the post-publication era.

In developing (frontier) equity markets, Zaremba et al. (2019) investigate factors that can explain the anomalies in frontier equity market returns. While their approach is judicious and thorough, they are merely asking the nested models to explain the anomalies in the returns and judge the performance of the model based on GRS test and Sharpe ratios. They, for instance, fail to identify which specific factor or set of factors account for differences in returns and risk premiums in returns in their set of markets. Their study also lacks the procedure to identify

among the significant factors, which one has more incremental value in describing the cross-sectional differences in returns.

There are many examples like these in the empirical asset pricing literature. Bryzgalova (2015a) and Harvey and Liu (2018) conclude that the majority of the discovered asset pricing factors are spurious. Perhaps, the failure of these empirical exercises in asset pricing is caused by tests that do not distinguish between two important categories of risks highlighted earlier. And as a result, numerous discoveries may be caused by authors not being methodologically clear on what their results are based on. Data mining has in this regard specifically been pointed out to as a significant impediment.

For this reason, Kelly et al. (2019) asserts that "…*a genuine risk factor must be related to the covariance matrix of returns, must be priced in the cross-section of returns, and should yield a reward-to-risk ratio that is reasonable enough to be consistent with risk pricing"*. Unfortunately, most studies in asset pricing do not attempt to relate identified factors with the covariance matrix of returns which makes it difficult to distinguish between 'characteristics' in returns and the real priced risk factors (Pukthuanthong et al., 2019). Cochrane (2009) suggests a theoretically, but empirically tractable asset pricing method to price all the financial assets in the market. While incorporating the assumption of no-arbitrage opportunity, Cochrane (2009) argues that an assets payoff can be represented in the form of equation (4);

$$p_t = E(m_{t+1}, x_{t+1}) \tag{4}$$

where $p_t$ is the price of an asset, $x_{t+1}$ is the future payoff of the stock, and $m_{t+1}$ is a stochastic discount factor (SDF), also referred to as the intertemporal marginal rate of substitution of consumption and as the pricing kernel. Cochrane (2009) maintains that the SDF procedure can be used to evaluate any asset in the market. The approach, therefore, has the ability to encompass many of the asset pricing models such as CAPM, Consumption CAPM, APT, and the Intertemporal CAPM. Given this generality in application, the stochastic discount factor

(SDF) $m_{t+1}$ can thus be presented in a multifactor pricing model to accommodate all the factors expected to be identified in this study. Assuming the existence of the no-arbitrage principle, the stochastic discount factor $m_{t+1}$ exists for any asset returns, $r_{i,t}$, such that:

$$E_t[m_{t+1}r_{i,t+1}] = 0 \tag{5}$$

$$m_{t+1} = \beta \frac{u'(C_{t+1})}{u'(C_t)} \tag{6}$$

where $m_{t+1}$ is the stochastic discount factor or the pricing kernel $u'(C_{t+1})$ is marginal utility function of one period ahead consumption or time $t+1$, while $u'(C_t)$ is the marginal utility at time $t$.One period return can be expressed as $E_t[r_{i,t+1}] = \frac{Cov(m_{t+1},r_{i,t+1})}{Var_t(m_{t+1})}\left(-\frac{Var_t(m_{t+1})}{E_t(m_{t+1})}\right)$ the first term in the right-hand side corresponds to $\beta_{i,t}$ which is a loading on systematic risk factor exposure and the second component on the right of the equation correspond to $\lambda_t$ defined as the price of risk associated with the factors. It follows that, in the stochastic discount factor (SDF), $m_{t+1}$, the risk factor loading is a linear relationship with risk factors, $f_{t+1}$. Without loss of generality, a simple linear combination of the factor loadings and factor risks for the $r_{i,t+1}$takes the form;

$$r_{i,t+1} = \alpha_{i,t} + \beta_{i,t}f_{t+1} + \varepsilon_{i,t+1} \tag{7}$$

where $E_t(\varepsilon_{i,t+1}) = E_t[\varepsilon_{i,t+1}f_{t+1}] = 0, E_t[f_{t+1}] = \lambda_t$, and $\alpha_{i,t} = 0$ for all $i$ and $t$.

Equation (7) is the launching pad for any asset pricing model. The equation has yielded a number of controversies, especially in its empirical implementation. Theoretically, mean-variance efficiency achieves the objectives of (7) by imposing a zero-value restriction on the first term of the equation, the alpha ($\alpha$). The risk factor $f$ is expected to price all the securities in the market.

An observation can be made about the modelling approaches used in the literature to determine the optimum $\beta_i f_{t+1}$ in (7): there is a dedicated group of researchers who perform dimensionality reduction of the many observed and tested risk factors using portfolios

constructed on those characteristics. For example, the strand that follows Fama and French (1993) style constructs portfolios related to the observed size and value characteristics. This group of researchers traces the transition of firms within a portfolio by rebalancing the portfolio at the beginning of every year.

Another strand of literature appears to accept that factors existing in the literature somehow have valid and sufficient explanatory power to predict returns. However, some of the factors might be highly correlated with each other to the extent that a statistical dimensionality reduction technique is required to address the high correlation problem. This group of researchers employ conventional dimensionality reduction techniques such as principal components, usually with modifications (Vanhatalo and Kulahci, 2016; Vanhatalo, Kulahci, and Bergquist, 2017).

Efforts have been made in the recent asset pricing literature to model the right-hand side of the equation separately, such that, if say three factors are deemed important in determining equity returns, regressing two of the factors on the first factor should yield a non-zero coefficient of the first term in equation (7), a procedure that has been labelled as spanning regression tests. Fama and French (2017) maintain that a factor whose average return is fully explained (the intercept is indistinguishable from zero) by the average returns on the other factors in a spanning regression is redundant and should not be considered for asset pricing.

On the other hand, the left-hand side procedure involves regressing the right-hand side factors on the left-hand side which canonically should produce a coefficient of zero for the first term in equation (7). Kelly et al. (2020) proposes the use of Instrumented Principal Components Analysis (IPCA) to identify the right factors from the list of possible RHS factors. The method is able to distinguish between two sets of factors relevant to asset pricing. The first set is the group responsible for common movement in stock prices; they are pervasive. The second set involves factors that move prices but are not associated with systematic risk premiums. They

specifically note that, although these factors do not necessarily have associated risk premia, the fact that they alter return differentials make them viable candidates for investment considerations by the market participants. In the same breadth, Pukthuanthong et al. (2019) also employs an elegantly crafted empirical protocol to identify among the real risk factors in asset pricing to evaluate equation (7). Their method, which we employ in this study is able to distinguish factors that drive returns from the ones that actually command risk premium.

### 3.4 Empirical Strategies

The preceding section has explored the theoretical basis for asset pricing. Equation (7) as discussed forms the basis for this study. This section thus deals with strategies to implement equation (7), with the assumption that there is a gamut of risk factor to span the model.

The study uses a triangulation approach to ensure a high degree of robustness of the identified factors. The approach begins with a procedure proposed by Pukthuanthong et al. (2019) which employs a set of necessary and sufficient conditions in factor identification. Necessary conditions identify factors related to the covariance matrix of returns, that is, factors that move returns and are related to the total volatility of returns. This group of factors is important for investors, since they present opportunity for arbitrage in case of mispricing. The ability to relate discovered risk factors to the covariance matrix of returns consequently offers a juggernaut starting point. The use of demeaned stock returns in this initial condition allows for the underlying drivers in returns to be *'sieved'* and grouped into few important drivers of underlying innovations in stock returns. The necessary condition is implemented through a dimensionality reduction technique, specifically Asymptotic PCA of Connor and Korajczyk (1988a) where demeaned individual stocks returns are subjected through Asymptotic PCA process then extract few components that describe majority of the return variance. These few components extracted are then subjected through Canonical Correlations Analysis (CCA) to calculate maximum linear combination of the return covariances and a group of candidate risk

factor ($g$ and $h$). The most desirable feature of this procedure is its ability to incorporate both constructed firm fundamental factors and macroeconomic risk factors in a single estimation procedure. Variable/factors that strongly correlate with the extracted principal components are treated as possible risk factors. Sufficient condition is achieved by conducting a formal asset pricing test to determine factors that actually command risk premiums. This is done through competing empirical asset pricing procedures such as Fama and MacBeth (1973) two-step regression procedure. The FM regression in this study is further complemented with a Generalised Method of Moments (GMM) type regression to cater for any stochastic distribution limitations in the data. Detailed descriptions of these procedures are provided in Chapter 4.

### 3.4.1 Factor Identification Protocol

The procedure adopted here is well outlined in Pukthuanthong et al. (2019) which comprise of necessary and sufficient conditions as already discussed in (3.4). We start by specifying the typical regression model under this procedure:

$$r_{i,t+1} = \alpha_{i,t} + \beta_{i,t} g_{t+1} + \gamma_{i,t} h_{t+1} + \varepsilon_{i,t+1}, \quad (8)$$

$$\overline{r_i} = \lambda_0 + \lambda_i \beta_i + \lambda_i \gamma_i + \varepsilon_i, \quad (9)$$

In equation 8, $r_{i,t+1}$ is the excess return on asset $i$ at time $t+1$, $\alpha_{i,t}$ is the asset's abnormal return at time t, whose expected value is zero. In many empirical tests, the theoretical alpha has been statistically different from zero. It explains why CAPM, and its multifactor extensions have remained contentious in empirical evaluation and investment practice. There is a significant number of asset managers whose investment strategies exclusively rely on index tracking, hence the values of $\alpha_i$ have significant implication for their investment strategy. Alpha is also used to evaluate portfolio efficiency (Gibbons, Ross, and Shanken, 1989).

$\beta, and\ \gamma,$ in equation 8 are coefficients associated with the innovations of risk factors $g$ and $h$ respectively. According to equation 8, $g$ represents pervasive risk factors commanding significant risk premium, while $h$ factors important for returns variations but do not attract significant risk premium. It follows that both $g$ and $h$ are related to the covariance matrix of returns, influencing total volatility of returns. While $g$ factors are important and compensated for in the marketplace because they command substantial risk premium, $h$ factors, because of their significant relationship with total volatility, are very important for arbitrageurs. However, profit opportunities could also arise from characteristics that are associated with return differences but are not related to risk rather than from unpriced risk factors

The uniqueness of this study lies in identifying these two categories of factors, which both Pukthuanthong et al. (2019) and Kelly et al. (2019 designate as important for asset pricing, for developing countries. We believe that true identities of these factors contribute to both practice and knowledge in developing equity markets.

A process closer to this is presented also by Kelly et al. (2019), who postulate that factors such as the ones in our category $h$ are important for arbitrageurs in the marketplace because of their ability to move returns even if they may not command a sufficient risk-reward ratio worthy of compensation. The process adopted in this study closely mirrors the Pukthuanthong et al. (2019) procedure. The necessary condition as presented in Pukthuanthong et al. (2019) identifies the universe of factors $g$ and $h$ in our case. The process produces factors significantly related to the covariance matrix of returns. As highlighted by Pukthuanthong et al. (2019), the proces begins by collecting $N$ individual firms with complete stock price data then demean their returns to conform with standard procedures in litertaure, and also to weed out individual stock charatcteristics which may adversely influence moment conditions. The second procedure involves extracting a prespecified number of principal components (PCs), say $M$,

from the $N$ demeaned return series using principal components analysis (PCA) or asymptotic principal components analysis (APCA) of Connor and Korajczyk (1988b). In the third process, we compute canonical correlations[5] between candidate risk factors $K(g\ and\ h)$ factors and the $M$ eigenvectors of the extracted latent equity return series (PCs). This achieves the intended objective of determining correlation between latent vectors of $K$ factors and the covariance matrix of $M$ return series. The decision to accept or reject a factor candidate depends on the significance of correlation between $M$ eigenvectors and $K$ latent factor candidates. If a factor candidate does not portray a strong canonical correlation coefficient with the linear combination of $M$ eigenvectors, the factor is dropped from the analysis.

Testing the sufficient condition involves determining if the identified factor candidates are priced; that is, whether they command risk premium or not. This procedure follows Fama and MacBeth (1973) test procedure which involves running a time series regression using OLS then extracting betas that are used in the second pass regression.

### 3.4.2 Double Selection LASSO

The second approach, used for triangulation purposes, implements a procedure advanced by Feng et al. (2020) to "tame the factor zoo". Their procedure, Double Selection Least Absolute Shrinkage and Selection Operator (LASSO) dimensionality reduction based mechanism, is aimed at selecting the best linear combination of variables explaining innovations in stock returns. Feng et al. (2020), like the protocol of Pukthuanthong et al. (2019), present two sets of factors to choose important asset pricing factors from. The first group, they claim come from factors already described in ubiquitous asset pricing studies as important, and already established as true risk drivers. This group they name as $g$, while the other group comes from a universe of factors that have had questionable empirical ability to describe returns. This group

[5] It is a relationship between two or more latent vectors. See (Thompson, 2005) for a detailed description.

named $h$ potentially has many factors which may not present any meaningful relationship with the return generating processes but may still have some form of relationship with the risk-return process. The intuition underpinning Feng et al. (2020) approach is that $g$ group of factors may be presenting a tractable linear relationship with stock returns, while $h$ do not, but $h$ could be linearly related to the $g$ group making them potential drivers of innovations in $g$ and hence stock returns.

DS-LASSO simultaneously identifies asset pricing factors and tests the validity of the factors for their ability to command significant risk premium. The goal of the procedure is to identify asset pricing factors in two appealing steps; the first step identifies factors that are strongly and significantly related to the covariance matrix of returns (these factors move returns and command significant risk premium), while the second step are factors weakly related to the return matrix but are possible predictors of important risk drivers in return. The second step is crucial, because although factors identified in this step are modest predictors of returns, their exclusion may lead to a substantial omitted variable bias (Belloni et al., 2014).

The literature (reviewed in Chapter Two) has shown that in situations where there are potentially many predictor variables a possibility of ending up with spurious factors looms large. LASSO is a penalty-based dimensionality reduction method commonly used in model selection. Other dimensionality reduction techniques such as PCA, Kalman Filters and Bootstrap in asset pricing often concentrate on returns and risks of selected portfolio rather than the measurement accuracy of the estimated parameters (De Mol, Giannone, and Reichlin, 2008). Penalised regression procedures help to mitigate this (Fan and Li, 2006).

Using LASSO criteria strictly[6] in factor selection has also been faulted for rigidities towards finite samples (Gallant, Hong, Leung, and Li, 2021). Asset pricing research is nonetheless faced with asymptotic distribution challenges. The procedure is considered particularly effective because it first estimates the risk factors using the selection criteria of conventional LASSO then uses a two-pass regression procedure of Fama and MacBeth (1973) to assign the beta loadings to a particular risk premium. Therefore, given its ability to double check the selected variables and empirically evaluate their pricing significance, the procedure is preferred for this stage of the study.

The procedure employed in this study is summarised in the following simple processes;

a) First, run a cross-sectional LASSO regression on sample covariances from the list of universe factors ($h_t$) and individual asset returns then extract significant covariances that best explain the expected returns.
b) Second, run another cross-sectional LASSO using the extracted covariances of $h_t$ against the covariances (the covariance between returns and each $j^{th}$ factor of each of the $g_t$ ) $g_t$ group factors and extract factors whose exposures are highly correlated with the covariance matrix of $g_t$ and cross section of returns. The output of this stage ensures that the most significant factors affecting return variations are selected.
c) Run an OLS type regression (Fama-MacBeth) using the covariances extracted from the two processes and returns. The output of this exercise yields the true combination of factors priced in a particular market. Factor Beta loadings with $t > 2.00$ are considered priced in the returns.

[6] When the number of variables exceed the number of observations, lasso criterion is not strictly convex, and may struggle to identify a unique minimizer.

In addition, a simple linear SDF specification can be used to demonstrate how DS LASSO is achieved

$$m_t = \lambda_0^{-1}(+ - 1 - \gamma_g^T g_t - \gamma_h^T h_t) \quad (10)$$

Where $\lambda_0$ is equivalent to zero beta rate, $g_t$ is a $n \times 1$ vector of important factors (first group), $h_t$ is a $q \times 1$ vector of potentially important factors. Both $g_t$ and $h_t$are demeaned to allow factor innovations such that $E(g_t) = 0$ and $E(h_t) = 0$. Also $\gamma_g$ and $\gamma_h$ are a $n \times 1$ and a q$\times 1$ are respectively vectors of parameters. $\gamma_g$ and $\gamma_h$ are also referred to as SDF loadings of factors $g_t$ and $h_t$. Our task is to make inference of SDF loadings of preselected $g_t$ factors while accounting for the explanatory powered of $h_t$. Recall that $h_t$ are considered weakly related to the covariance matrix of returns but may be providing marginal explanatory power to the overall innovations in returns and $g_t$ factors. The goal is to avoid omitted variable bias.

In addition to the two factors, a vector $s \times 1$ of test portfolios are included. The expected returns of this vector can be expressed as

$$E(r_t) = l_n\lambda_0 + B_g\gamma_g + B_h\gamma_{h,} \quad (11)$$

Where $l_n$ is an $s \times 1$ vector of 1s, $B_a = Cov(r_t, a_t)$ for $a = g, h$ or some random term $v$

### 3.4.3 Other competing Empirical strategies

There are other elegant empirical strategies in asset pricing capable of producing similar empirical outcomes as the ones preferred and adopted in this study. In this subsection, therefore, we highlight to some detail some of these strategies. We cannot be able to apply all of them but appreciating their capabilities in arriving to a sort of conclusion we envisage here is considered as justice.

**a) Instrumented Principal Components Analysis (IPCA)**

The IPCA uses firm characteristics as instruments and latent variables in explaining differences in stock returns and common sources of risk. According to Kelly et al. (2020), characteristics line up with average returns because they proxy for common sources of risk. The intention is to search for a small number of systematic risk sources (say $K$ factors) describing returns. The general model can hence take the form,

$$r_{i,t+1} = \alpha_{i,t} + \beta_{i,t} f_{t+1} + \varepsilon_{i,t+1} \quad (12)$$

The IPCA framework of Kelly et al. (2020) describes the treatment of both $\alpha_{i,t}$ (asset/portfolio alpha) and $\beta_{i,t}$ (loadings for the $K$ number of factors) in a unique and nuanced style. In many asset pricing tests, a pre-specified set of factors is often used to compute the values of $\alpha_{i,t}$, where the closer it is to zero, the higher the validity of the proposed factors.

Given the implications of $\alpha_{i,t}$ and $\beta_{i,t}$, and the modelling requirements of IPCA, the two parameters are individually expressed as

$\alpha_{i,t} = z'_{i,t}\gamma_\alpha + u_{\alpha,i,t}$ and $\beta_{i,t} = z'_{i,t}\gamma_\beta + u_{\beta,i,t}$ where $z_{i,t}$ is $L \times 1$ vector of instrument variables, $\beta_{i,t}$ is a dynamic factor loading on $K$-vector of latent factors $f_{t+1}$. $\beta_{i,t}$ specification has an instrumental implication to their model. By instrumenting estimation of latent factor loadings with observable characteristics, the procedure allows for the inclusion of a large number of firm characteristics to shape the factor returns. It also permits time-varying instruments (characteristics) making it possible to model conditional returns. $\gamma_\beta$ hence maps the characteristics from a large number of characteristics to a few risk factor exposures. Matrix $\gamma_\beta$ describes a parsimonious linear combination of characteristics that capture complete information of the latent factor loading structure.

By specifying the parameters of this model as ($\beta_{i,t} = z'_{i,t}\gamma_\beta + u_{\beta,i,t}$), it becomes practical to address the problem of noisy characteristics by isolating the noisy ones and loading them into $u_{\beta,i,t}$ (the error term). This also addresses the problem of migrating assets, a property that arises due to evolving nature of stocks over time as they change their fundamentals causing them to

move from small to big, low profitability to high profitability, low book-to-market to high book-to-market stocks and so on. The evolving characteristics of assets has provided a considerable challenge in modelling firm-level conditional expected returns on stocks. Fama and French (2015) capture this through portfolio rebalancing, where at the end of each year, using the various breakpoints, stocks are allocated to big-small, high-low, robust-weak etc.

**b) Bootstrap technique**

Ordinarily, one would resort to simple dimensionality reduction techniques such as Principal Component Analysis, where PCA employs orthogonal transformation in identifying among linearly correlated variables, then combining them into a single component or factor. However, conventional PCA is questioned for its ability to model conditional versions of asset pricing and cross-sectional dependence structure commonly found in financial time series data. PCA is also limited to the extent that it does not deal with autocorrelation in returns,[7] which is common for the type of markets under consideration in this study (Lettau and Pelger, 2020; Richman, 1986). The Instrumented Principal Components Analysis (IPCA) discussed above may resolve some these shortcomings by allowing for dynamic behaviours of returns while at the same time making use of a large number of firm level characteristics as instruments to proxy for both systematic risk drivers and returns variations.

As an alternative to IPCA, Harvey and Liu (2021) employ bootstrap to choose important risk drivers from a large group of asset pricing factors. Use of bootstrapping in asset pricing they claim is robust and provides valid confidence bounds especially in situations where asymptotic properties are questionable. Bootstrap method, as they present also addresses data mining

[7] This is because PCA does not account for serial autocorrelation in the series, but multidimensionality. Vortelinos (2017) note that for PCA to be able to model volatility and autoregressive processes, it must be augmented to include combining method of forecasting, or alternatively use Dynamic PCA.

problems[8] prevelant in asset pricing tests (White, 2000). Data mining[9] according to Sullivan, Timmermann, and White (2001) and Harvey and Liu (2021) can influence hypothesis testing resulting in spurious factors being identified.

***Motivating the Bootstrapping Method***

The procedure of Harvey and Liu (2021), mirrors Gonçalves and White (2004) and Bryzgalova (2015a). These authors seem to be influenced by the insights of White (2000) on how to addess data series which exhibit significant time dependence structure. Block bootstrap as applied by Harvey and Liu (2021), is praised for its ability to capture time-series dependence through sampling with replacement.

The Harvey and Liu (2021) procedure involve three important processes namely, Orthogonalization, Bootstrappping and hypothesis testing that allows for evaluating whether optimality has been reached. By optimality, it means that the most significant return drivers that adequately explain both factor and return covariances, return differentials and risk premium have been identified. The ability of the procedure to deal with cross-sectional dependency among variables, which in turn aid in avoiding repeating redundant variables in the regression equation is highly celebrated (Little, Bovaird, and Widaman, 2006). This attribute can significantly contribute to model selection and boosts models' prediction efficacy (Clyde, Desimone, and Parmigiani, 1996).

***i) Orthogonalization and Bootstrapping***

[8] Data mining refers to multiple searches in the data for predictor variables, then using the same data to evaluate the model without accounting for number of searches (Ferson, Sarkissian, & Simin, 2008). It can lead to wrong hypothesis testing and spurious regressions.

[9] Sullivan, Timmermann, and White (2001) contend that use of same data to test the hypothesis can lead to making both type one and type two errors. One, type I error in the sense that testing wrong factors that result with high significant statistical summaries like P-values and higher $R^2$. The type II error is when a good or theoretically significant factor is actually dropped or neglected in the model just because it does not result in higher statistical significance.

In performing the bootstrap to identify priced factors, Harvey and Liu (2021) employ a predictive regressions approach. Starting with a matrix $(T \times N)$ of $Y$ returns and matrix $X$ $(T \times M)$ of predictor variables, their goal is to bootstrap true predictors within the $X$ matrix. Define $M$ as the maximum number of significant factors in $X$, and let a subset of $M$ be a vector $(T \times 1)$. As an illustration, in order to pick the 'best' predictive regressors, let the pre-selected variables for the predictive regression be $k$ and given the goal of extracting any other variable from $X$ $(T \times M)$, we look for any other variables that are important after selecting $k$ to include in the model. $M - k$ is, therefore, the optimal number of predictor variables needed, but it is not certain if their statistical contribution to the model is sufficient for their inclusion in the model or not, therefore, from $M - k$ matrix, we extract the significant variables and maintain their interdependence structure through the orthogonalization process. The new $M - k$ variables must be orthogonal to $k$ so that it is possible to determine if the new information or explanatory power of these variables actually affect the variations in the returns of $Y$. Thus, $Y$ is projected onto the pre-selected $k$ then extract the resultant residuals (the proportion of returns not explained by the $k$ variables) as,

$$Y = \omega_k + \lambda_k X_k + \epsilon_k \tag{13}$$

The next step involves projecting the $M - k$ variables one by one on the residual of the first regression and extracting new residuals at each stage. This process ensures that the new variables ($M - k$ residuals) are uncorrelated with the pre-selected variables, $k$. A restrictive hypothesis[10] to guide this process is therefore provided for the $M - k$ variables that, none of the $M - k$ variables is considered true in in-sample to account for the variations in $Y$[11]. This

[10] This allows for testing all the suspect variables. It is the reason for conduction Orthogonalization process so that every variable's information is independently extracted, to be able to judge their individual explanatory power. The restrictions will be implemented by running block bootstrap through time.
[11] The process follows the Harvey and Liu (2015) procedure

restriction is important in controlling for multiple testing and data mining biases. Therefore, the extracted residuals from (13) can be written as $Y_k^e$. The next step involves projection of the next variable randomly selected from the pool of $M-k$ and extracting their residuals. Let the next variable be $l$ ($l \in X$), then $X_l$ is the new variable to project onto the residuals of (12).

$$X_l = \omega_l + \boldsymbol{h_l Y}_k^e + \epsilon_l \tag{14}$$

The residual $X_l^e$ is extracted out of regression (14) and considered a possible important explanatory variable in the asset pricing equation describing variations in $Y$. At this stage, it is still abstract to pinpoint what this group of $M-k$ is, but the variables come from the empirically identified variables in the literature of asset pricing, that have been consistently identified as risk drivers in asset return valuation. It is important that only factors that account for the covariance matrix of returns should be included in the list.

To generalize this process of orthogonalization for the whole set of $M-k$ predictor variables, equation (15) shows how the variables are orthogonalized as a preparatory process for inclusion in the bootstrap computation

$$\boldsymbol{X}_{k+n} = \omega_n + \hbar_n Y_k^e + \boldsymbol{X}_{k+n}^e \, , n = 1, 2, \cdots, M-k \tag{15}$$

where $\omega_n$ is the intercept, $\hbar_n$ is the slope and $\boldsymbol{X}_{k+n}^e$ is the residual vector for all the $M-k$ variables. The process ensures that the orthogonalized right hand-side variables have zero correlation with the residuals from the first projection between the predictive pre-selected variables and the returns ($Y$). After undertaking the Orthogonalization process to eliminate any correlation of the anticipated variables and the fundamental pre-selected variables, the next process is to bootstrap through time again to generate empirical distribution of the summary statistics for the various regression models, see Harvey and Liu, (2021) for further details.

Proceeding to a general set up where the extraction of the important variables takes place, it is important to re-introduce the guiding test hypothesis. The hypothesis states that $M-k$ variables are not significant for the in-sample regressors. It, therefore, involves running regressions with all the $M-k$ variables. Each of the $M-k$ regressions must entail projecting $Y^{e,b}$ onto each individual candidate variables from the data matrix $X^{e,b}$. Let the statistic for evaluating the associated contribution of any incoming variable be $\theta$ for instance, $\theta_{k+1}^{b}, \theta_{k+2}^{b}, \theta_{k+3}^{b}, \ldots, \theta_{M}^{b}$ and letting the maximum statistic take $\theta_{I}^{b}$, the processes is able to evaluate incremental value of any incoming variable. $\theta_{I}^{b}$ can be any measure of model fitness normally used to adjudicate model suitability. Two statistics, $R^2$ and $t$ are used to evaluate the significance of the slope in the cross-sectional regression. The choice of significant variables is entirely based on values of the two statistics.

From the null hypothesis that none of the $M-k$ variables are important in-sample predictors of $Y$, it is possible to control for multiple testing and data mining biases. It is important that the test of significance of variables or factors do not depend on any *apriori*. The statistics identified earlier preclude insignificant variables from entering the model. Thus, one initially examines the contribution of the incoming variable to the model, and if this contribution is not significant as per the statistic, the variable falls off the list, and the next variable is tested. This procedure goes on until all the $M-k$ regressions are tested. To test whether the variables selected are indeed significant for the asset pricing model, the next stage involves hypothesis testing.

### *ii) Hypothesis Testing*

The interest of this procedure lies in the ability of the regressor matrix $X$ to significantly predict the variations in the $Y$ vector of returns. From the preceding discussion, it has been presented

that the statistic $\theta_I^b$ is to be employed to measure the incremental contribution of any incoming variable within the $M$ −k group. Now, in order to select a variable from this group, the exact contribution of a candidate variable must be obtained. This is done through testing the $(k+1)^{\text{th}}$ significant predictor using a new summary statistic which can be denoted as $\theta_I^d$. $\theta_I^d$ is compared with the original summary statistic $\theta_I^b$ from the Orthogonalization process. If, let say the significance level of a parameter $\beta$ is specified as 5%, then rejection of the null hypothesis is considered when $\theta_I^d$ exceed $(1-\beta)$. Let the total bootstraps are denoted as $(\theta_I)^B$, then the decision of rejection or acceptance is taken on $(1-\beta)^{\text{th}}$ percentile of $(\theta_I)^B$ as;

$$\theta_I^d > (\theta_I)^B_{(1-\beta)} \tag{16}$$

where $(\theta_I)^B_{(1-\beta)}$ is the $(1-\beta)$ percentile of $(\theta_I)^B$. The final outcome from the hypothesis test helps to conclude whether there are any significant predictor variables within the $M-k$ group, and as well when to stop, let us say we have up to 100,000 bootstraps.

### *iii) Time series and Cross-sectional dependence*

So far, the discussion has been based on the variables expected to be important predictors in the proposed model. Asset pricing theory, however, is based on finely constructed factors, therefore, the discussion can now shift to factors extracted from the bootstrapped procedure. Orthogonalization of the variables helped to limit the contemporaneous effects of the variables and ensured that only true risk factors are selected. At this stage, the same way, the factors are demeaned so as to gauge their own pure effects by limiting both the time series and cross-sectional dependence problems. For illustration, consider a one-factor time series model:

$$R_{it} = \alpha_i + \beta_i f_{it} + e_{it},\ i = 1,2,\cdots,N \tag{17}$$

Where $R_{it}$ is excess return on asset $i$, $\alpha_i$ is the time series regression intercept or commonly known as the alpha, $\beta_i$ is time series regression slope of the one pricing factor $f_{it}$. In this model,

if the intercept equals zero ($\alpha_i = 0$), then $R_{it} = \beta_i f_{it}$, and the market factor, ($f_{it}$=$R_{mt} - R_{ft}$), is the only priced factor.

In our application, $f_{it}$ is first demeaned or orthogonalized, and the resultant factor, $f^d$, has all the time series features of $f_{it}$, but does not have any explanatory powers on the cross-sectional variations of the expected returns. The new factor is then bootstrapped to obtain new statistical distributions that summarise the pricing errors in the original factor, and then compare their realized statistics, i.e., $t$ −stats and $R$ −squares.

This procedure is used for any candidate risk factors in the analysis. In all the $M$ factors and $M - k$ factors, we can choose to test all the incoming variables on the $k$ preselected variables until we exhaust all the factors. In the event that a second factor is introduced into the model of equation (16), the expectation is that the new intercept still equals zero if the introduced factor is significant or priced, and the use of a summary statistics such as $R^2$ and $t - stat$ can help to determine if the incoming variable has adequate explanatory power. The null hypothesis set earlier that the incoming variable has zero impact on the model is still upheld, hence treating the incoming variable as not significant *apriori*. If we have one preselected factor in the equation as,

$$R_{it} = \alpha_i + \beta_{i1} f_{1t} + e_{it} \tag{18}$$

Equation (15) can therefore be treated as the baseline model, and with the new factor set to be included in the equation, the resultant equation can be written as

$$R_{it} = \alpha_i^* + \beta_{1i} f_{1i} + \beta_{i2}^* f_{2t} + e_{it}^* \tag{19}$$

Expectedly, the new intercept should equal the intercept in (18) which is equal to zero ($\alpha_i^* = \alpha_i = 0$). This involves testing the hypothesis on the contributory power of the new variable to the model, which is done repeatedly until the last factor is identified.

### 3.5 Test Portfolios and Factors Construction

It is claimed that inability to construct efficient portfolios could be at the forefront of reasons why CAPM empirical evaluation is inconclusive (Fama and French, 2004; Huberman and Kandel, 1987). Construction of both test and factor portfolios in this study uses the intuition in Fama and French (1993, 2015) corroborated with the new insights in many studies reviewed in the literature chapter of the study. The procedures are partly guided by the nature of markets in the sample under investigation. For example, the Fama and French procedures are slightly adjusted to fit few datapoints, hence instead of using the commonly implemented method of splitting the market cap at the median value, we use 10 to 90 and 30 to 70 in some cases to represent the small and big cap firms. Elaborate description of the process and procedure for constructing all the variables to be used in the empirical implementation are presented in Chapter four. Table 4 documents, in detail, the construction of test portfolios and factor portfolios.

It is worth noting that the portfolios used in this study are constructed for Developing markets, emerging markets, developed markets. There is also an attempt to construct a global portfolio comprising of all the countries considered in the sample. This is done to also provide comparative analysis.

We also consider a slight change introduced by Pukthuanthong et al. (2019) who uses a double-sorting criteria where stocks are sorted into 10 portfolios based on firm size, then for each size decile, the stocks are sorted by market beta, and subsequently the betas of all the factors that

survive the dimensionality reduction procedure. For this section of the study, this procedure is implemented for test portfolios only.

### 3.6 Macro-Based Asset Pricing

For completeness, this study uses the two competing asset pricing paradigms to evaluate the price of risk in developing equity markets. The paradigm discussed here is specified under the macro approach of Arbitrage Pricing Theory (APT) to theoretically and empirically carry out asset pricing research using pervasive state factors. An interesting proposition in this section of the study is about the possibility of several systematic state factors influencing risk and commanding significant risk premiums in returns of developing equity markets. The APT platform, although elegant, has been criticised for not providing a way for disclosing the identities of the so-called pervasive factors that influence return variations. Consequently, consensus building on the right identity of the candidate factors in equity markets have remained modest. Many attempts employ factor reduction techniques to search for the real factors underpinning APT from a large group of macroeconomic variables.

While APT and CAPM may share certain underlying principles, CAPM is mainly criticized for restricting risk associated with returns to one technically unobservable factor, whereas APT permit many factors to span risk structure in the stock markets. As a result, methodological differences emerge when the two theories are empirically evaluated. Proponents of APT such as Dybvig and Ross (1985) charge that while the model imposes a dimensionality restriction on the risky part of the returns, CAPM does not. They contend that the APT is more general than CAPM in the sense that the factor prices in the model do not have to bear special relations to the CAPM's market factor loadings and the portfolio-based asset pricing procedures, commonly found in asset pricing anomalies.

### 3.6.1 The Arbitrage Pricing Theory: Estimation issues

According to Ross (1976), the fact that whenever market goes up, majority of the stocks go up, but there are significant number of stocks that take a different direction, signal a possibility of pervasive underlying return drivers other than the market beta as prescribed by the CAPM. However, a commonly cited weakness of the APT is that it does not clearly prescribe the econometric procedure or theory-based method to identify the said *k* risk factors that form the vector, $f_{it}$ (perversive risk factors). Researchers have made propositions to deal with this weakness, and in particular for this study, a protocol of Pukthuanthong et al. (2019), complimented with Connor and Korajczyk (1988b) asymptotic principal components analysis, is applied. Both are, essentially, dimensionality reduction techniques, where common highly correlated variables are combined to form uncorrelated latent factors. These latent factors are therefore considered the main risk drivers relevant in understanding the risk-return relations in the market.

We implement the two mentioned procedures because, ordinarily, PCA is commonly faulted on its rigidity to model dynamic series. Time-varying volatility, heavy tails and ultimately non-parametric behaviours of most stock return series are central to describing the underlying relationships, therefore, ignoring them may distort principal components from the latent factors (Aït-Sahalia and Xiu, 2019). The distortionary effects could even be stronger in the set of markets under investigation here. For instance, Kodongo and Ojah (2011) do not find unconditional version of exchange rates risk priced in African stock markets, but Kodongo and Ojah (2014) find conditional version of exchange rates command significant risk premium in African stock markets. Using this precedence, then Dynamic Factor Analysis (DFM) would naturally be adequate to deal with the non-parametric tendencies in the data series in this study, which were partly the reason why Odongo and Ojah (2011) failed to unconditionally describe asset pricing risk in African countries using exchange rates.

As has been established in this study through literature, data paucities in developing equity markets, evolving characteristics of macroeconomic variables, scarcity of data on sectoral variables are significant impediments to using standard factor reduction techniques like PCA. Stock and Watson (2011) nonetheless emphasise that only a few factors can be used to explain significant variations in many macroeconomic, financial, and sectoral series. That is, it is possible to combine regressors from a large pool to few representatives that can explain as much of the variations as the entire pool would, with significant precision. It would be best to employ DFM to help identify from a large pool, the significant regressors that form the $f_{it}$ in the model. DFM is also not free of challenges, its main shortcoming is the generalization associated with latent factors.

An example of a factor Analytical model can be presented as;

$$R_{it} = \omega_{it} + \lambda_i f_{it} + e_{it} \quad (20)$$

In this model, factor loadings converge in $\lambda_i$ which can also be defined as weight that asset $i$ put on corresponding factor $f_i$ at time $t$, or the exposure of the factor risk (systematic risks). The dimensional reduction ensures that an optimal combination of orthogonal vectors is derived to form $f_t$.

### 3.6.3 Alternative view: Using Mimicking Portfolios of Macroeconomic Factors

The theoretical motivation of APT is that a large group of pervasive state factors are important in determining systematic innovations in asset prices. Among this group of macro factors, a sizeable number of them have weak correlation with asset prices hence produce almost insignificant results in asset pricing. Kleibergen (2009) assert that when factors are only weakly correlated with asset returns so their betas are small, the inference on risk premia using the Fama-Macbeth procedure may be spurious.

Instead of using the original macroeconomic factors, their mimicking portfolios are also widely used to replace the pre-specified macro factors in asset pricing studies. Breeden (1979) and Huberman, Kandel, and Stambaugh (1987) provide the theoretical justification for this and establish that factors can be replaced by their mimicking portfolios for asset pricing tests. In terms of macroeconomic factors, the common method of constructing their mimicking portfolios is to project the factors on a set of base assets that span the asset space through a time series regression. The output of this process ensures higher correlation with asset returns which eventually improves their betas if an asset pricing test is carried out. The projection could be interpreted as de-noising[12] the macroeconomic factors so that their true effects can be realised in asset returns (Adrian, Etula, and Muir, 2014).

Mimicking macroeconomic portfolio has its own shortcomings and could suffer from data mining just like the portfolio-based approaches. If mimicking portfolios result from the projection of factors with small betas on base assets, then empirical findings based on such mimicking portfolios need to be viewed with caution. The authors point out that when the betas of macroeconomic factors are small, the betas of their mimicking portfolios can be spuriously large. Hence, using mimicking portfolios instead of macroeconomic factors for asset pricing does not necessarily imply improved inference on risk premia or more generally, improved performance of asset pricing tests. Therefore, this procedure is not used for the empirical analysis on this study; we highlight it as a competing paradigm in trying to identify the most important factors in asset pricing which is crucial to this study.

[12] Recent studies use wavelet procedure to remove undesirable effects in data. Others use de-noising, a process geared towards removing the effects of undesirable attributes in the data such as autocorrelation and serial interdependence (Chicheportiche & Bouchaud, 2015; Hu, Pan, & Wang, 2013; Lin, Yang, Marsh, & Chen, 2018).

### 3.6.4 Strictly Taking the APT route - empirical implementation

The APT procedure discussed in the preceding section use multifactor pervasive state variables in developing equity markets to evaluate their ability to price risk. Empirical evaluation of APT as applied in this study also intends to address the market integration hypothesis by including international macroeconomic variables cited in extant asset pricing literature with some degree of influence on cross border trading and international portfolio diversification. Equation (19) is more of theoretical than empirical relationship. Nonetheless, the equation is used to describe relationship between macroeconomic risk factors and stock returns $R_{it}$.

$$R_i = \alpha_i + \sum_{d=1}^{D} \beta_{i,d} F_k^K + \sum_{h=1}^{H} \delta_{i,h} F_h^H + \varepsilon_i \qquad (21)$$

$R_i$ is the vector of $M$ individual stocks returns, $\alpha_i$ is constant providing test for efficiency of the selected factors in explaining the asset returns, in many asset pricing tests, especially the mean-variance efficiency criterion, the closer the estimated values of $\alpha_i$ to zero, the better the ability of the right-hand side factors in explaining return variations. Since we are not assuming the integration, $\beta_{i,d}$ is the coefficient of the domestic variables category that are considered important in describing risk-return relations, and $\delta_{i,h}$ is the coefficient of global macroeconomic risk factors. $\beta_{i,d}$ measures the sensitivity of frontier markets returns to domestic factors, while $\delta_{i,h}$ measures the sensitivity to global factors. $\alpha_i$ is theoretically expected to be zero if the factors included in the model adequately describe returns of developing countries stock markets. $F^D$ and $F^H$ respectively denote the possible universe of domestic and global factors included in the analysis.

Domestic macroeconomic variables that form $F^D$ include inflation, aggregate liquidity, governance variables, broad market volatility, and money supply. While global variables include agricultural commodity index, global consumer confidence indicators (US). Consumer

confidence), global debt variables (term spread and term premium), metal index, proxy for global market index, oil prices, trade weighted exchange rates, and global volatility index (VIX).

# CHAPTER 4

# EMPIRICAL IMPLEMENTATION AND ANALYSIS

## 4.1 Introduction

This chapter presents the implementation of empirical strategies proposed and discussed in chapter 3. The analyses employed in this chapter utilize nuances in recent studies such as Jegadeesh, Noh, Pukthuanthong, Roll, and Wang (2019), Zaremba and Maydybura (2019), and Pukthuanthong et al. (2019). Jegadeesh et al. (2019) for instance, demonstrate how to deal with Errors-in-Variables (EIV) problem.

This chapter begins with a pertinent description of the data used. Given that this study is quite data-driven, the large volume of data used are stratified into sub-categories, depending on their intended application. The first section describes the individual country stock returns, which sheds light on the number of firms drawn from a specific country. This is followed by a description of basic features in each country's stock price data before determining the underlying drivers of return. For this, the study employs recently proposed[13] statistical procedures such as Asymptotic Principal Components Analysis (APCA) and Canonical Correlations Analysis (CCA), both of which are described in Chapter 3. It is only after a clear identity of candidate risk drivers is established that a formal statistical test of the surviving candidate risk factors and accompanying statistical influence on stock returns are carried out.

## 4.2 Data Description

Volumes of asset pricing research have since established that empirical asset pricing is a highly data-driven exercise. The evidence adduced by seminal asset pricing research papers like Fama and MacBeth (1973), Fama and French (2012), Fama and French (2015), Fama and French

[13] According to our knowledge, the procedures have been in existence, but have rarely received attention among economic and finance researchers.

(1993), Chen et al. (1986), Amihud and Mendelson (1986a), Harvey and Liu (2018), Feng et al. (2020), Novy-Marx (2013), Harvey and Liu (2019a) and Kozak et al. (2018) among others illustrate practically how success in asset pricing research closely hinges on a large volume of financial asset data spanning over a long period of time. In less developed markets, due to lack of sufficient data, pooling techniques are often favoured to allow diversification in constructing asset pricing factors and test portfolios (Boamah, 2017; Zaremba and Maydybura, 2019; Zaremba and Umutlu, 2018).

However, pooling techniques are usually plagued with assumption that all the markets have similar characteristics. This is often not the case as differences such as accounting reporting standards and market infrastructure inadequacies exist. In this study, such inadequacies are addressed by allowing the factors or variables to retain specific country status. For example, if a firm appears big or small at country level, the firm must retain the status at the pooled sample level.

The examples of studies cited in the preceding paragraph, except for the less developed market studies, tend to use monthly data frequency spanning three decades and beyond. Furthermore, majority of the tests, with the exception of developing markets, are conducted in large, and well-developed stock markets like New York Stock Exchange (NYSE), American Stock Exchange (AMEX), Canadian Stock Exchange, London Stock Exchange, Tokyo Stock Exchange, Nasdaq, and others of the same calibre which use sophisticated trading infrastructure, have high frequency of trading, employ advanced trading technology, and have sufficient archives of high quality financial asset data (Hung and Lien, 2019). Other studies around the world, especially in frontier and emerging stock markets, struggle to meet these yardsticks, hence have had to contend with a paucity of quality data spanning long periods of time (see Alhashel, 2019; Blackburn and Cakici, 2017; Boamah, 2017; Zaremba et al., 2018a; Zaremba and Maydybura, 2019; Zaremba et al., 2019).

Considering the highlighted differences in data availability, the current study uses data per country from their earliest availability. Chapters 1, 2, and 3 of this study explore possible data asymmetries across the sampled countries. Thus, the sample used for this study consists of 20 developing countries with complete equity market data at varying times of reporting. For instance, Nigeria and Mauritius have very few firms with complete data at the start of the sample, but become consistent from 2007 and 2009, respectively. At the country level, this shortcoming impacts the ability to construct a long memory firm characteristic factor, although this is a ubiquitous problem in developing markets. Moreover, where countries have incomplete information on firm fundamental variables at the inception of the sample, the required data are proxied by the median values of similar variables in countries with such information. This procedure has been successfully implemented by Berger, Pukthuanthong, and Yang (2011), who conduct a comprehensive analysis of asset pricing in frontier equity markets with significant data challenges and use median values of the markets with complete information to proxy similar markets with incomplete data. For instance, should Nigeria, Kenya or Mauritius miss data on profitability, while the rest of the 20 countries have this information, we take a median profitability value of the 17 countries to proxy profitability for the three countries with missing information to construct portfolios. The procedure thus allow for construction of certain factors using information from countries in the same category provided stock price data are available. Other countries that would be affected by this shortcoming include Vietnam and Kazakhstan, both of which lack data on firm characteristics such as Market Cap, Book-to-Market, traded volume, and turnover required to construct factors for subsequent analysis. Therefore, to implement the procedure, we set the given country's sorting equal to the median level of all developing countries within the sample at that point in time.

To be able to achieve greater insights and to also account for potential microstructure problems (Landis and Skouras, 2021) in these markets, we adopt a relatively longer period of data using

monthly stock price data starting from January 1, 1996, to February 1, 2020, resulting in 290 months of observation. However, for some countries, firms are incorporated into the sample later than January 1996 as their data become available. Monthly stock price data are used to calculate individual stock returns intended for the first phase of the study, which involves determining the covariance matrix of returns. Determination of the covariance structure of returns is central to this study, as it is the first stage to uncovering the existence of multivariate risk drivers in stock returns. This is done through the Asymptotic Principal Components Analysis and standard PCA whenever data permit.

Existence of more than one significant Principal Component (CP) is an indication of the presence of more than one risk driver in the sample of the stock market under investigation. For ease of comparison, all firm characteristics data are converted to US dollars. All the firm fundamental variables and macroeconomic variables are sourced from Thompson Reuters DataStream. However, for the firm characteristic variables, the data from DataStream was visually compared with data from Bloomberg to establish the extent of disparity. We established no significant departure and consequently relied on DataStream for the data. For global macroeconomic variables, the same filter procedure was adopted where all the data sourced form DataStream were compared with those that come from individual country statistical outputs in dollar terms where applicable and Federal Reserve Economic Data (FRED)/Federal Reserve Bank of St. Louis

Table **3** compares markets included in this study in terms of the number of listed firms with complete data over the period of the study, average cross-sectional returns over the sample period, return variability measured by the standard deviation of the returns and the minimum and maximum cross-sectional returns realised by each market over the period of the study. The average market capitalisation is calculated as the combined average market size (capitalization) of all the firms in each country. Developing equity markets with available data between the

period of January 1996 to February 2020 are 20 in total, with data availability starting from the earliest January 2, 1996 (Argentina, Kenya, and Kuwait) to 1 February 2020. Emerging markets included here are 13, and developed markets are 9 in total.

Table 2**: Sample of Countries**

| Country | First Observation | Last observation | No. of Firm-Month Obs. | Av. No. of firms | Annualised Mean Return (%) | STD of Return (%) | Min Return (%) | Max Return (%) | Av. Mkt Size (USD '000) |
|---|---|---|---|---|---|---|---|---|---|
| Developing Countries | | | | | | | | | |
| Argentina | 1996/01/02 | 2020/02/01 | 17229 | 50.83 | 0.20 | 2.77 | -9.19 | 18.88 | 49993.91 |
| Bahrain | 1997/04/16 | 2020/02/01 | 7293 | 37.40 | 0.02 | 0.55 | -1.30 | 5.30 | 14785.02 |
| Bangladesh | 2009/03/02 | 2020/02/01 | 19603 | 148.51 | 0.08 | 2.95 | -6.78 | 15.81 | 25021.48 |
| Croatia | 1998/06/30 | 2020/02/01 | 24416 | 72.02 | 2.56 | 5.19 | -10.97 | 30.82 | 17535.12 |
| Jordan | 1997/10/16 | 2020/02/01 | 33167 | 97.84 | 0.39 | 3.41 | -1.28 | 36.21 | 28469.08 |
| Kazakhstan | 2004/05/21 | 2020/02/01 | 1797 | 9.51 | 1.38 | 3.50 | -14.90 | 27.00 | 6336.67 |
| Kenya | 1996/01/02 | 2020/02/01 | 14828 | 43.74 | -0.04 | 1.05 | -7.50 | 19.04 | 21411.27 |
| Kuwait | 1996/02/14 | 2020/02/01 | 39811 | 117.44 | 0.01 | 2.38 | -4.30 | 13.41 | 40584.62 |
| Lithuania | 1997/06/13 | 2020/02/01 | 7506 | 22.14 | 0.19 | 3.58 | -9.90 | 19.61 | 2551.71 |
| Mauritius | 2008/11/24 | 2020/02/01 | 12485 | 36.83 | 0.24 | 3.91 | -1.36 | 21.72 | 5120.42 |
| Morocco | 1997/01/02 | 2020/02/01 | 18417 | 54.33 | 1.98 | 2.08 | -1.69 | 21.10 | 51770.55 |
| Nigeria | 2001/01/03 | 2020/02/01 | 5441 | 23.86 | -0.07 | 0.74 | -7.40 | 9.61 | 36444.53 |
| Oman | 1996/01/02 | 2020/02/01 | 21781 | 64.25 | 0.22 | 2.01 | -13.00 | 15.82 | 18163.70 |
| Pakistan | 1997/03/05 | 2020/02/01 | 34368 | 130.18 | 0.09 | 3.66 | -5.85 | 18.66 | 34631.93 |
| Romania | 1997/10/02 | 2020/02/01 | 15477 | 53.55 | 0.45 | 3.94 | 6.79 | 48.18 | 10101.34 |
| Serbia | 2005/04/04 | 2020/02/01 | 16915 | 91.43 | 0.97 | 6.62 | 0.00 | 15.86 | 8319.82 |
| Slovenia | 1998/07/01 | 2020/02/01 | 11184 | 114.13 | 1.25 | 11.59 | 0.00 | 16.97 | 7924.06 |
| Sri Lanka | 2002/02/03 | 2020/02/01 | 16606 | 83.87 | 0.07 | 2.87 | -6.21 | 16.36 | 11264.04 |
| Tunisia | 1999/03/11 | 2020/02/01 | 13318 | 60.53 | 0.98 | 3.51 | -36.14 | 12.19 | 5876.50 |
| Vietnam | 2001/03/12 | 2020/02/01 | 47116 | 197.97 | -0.04 | 1.29 | -6.49 | 14.36 | 57515.28 |
| Emerging Markets | | | | | | | | | |
| Brazil | 1996/01/02 | 2020/02/01 | 55970 | 193.00 | -0.07 | 3.53 | -12.16 | 29.54 | 783342.28 |
| Chile | 1996/01/02 | 2020/02/01 | 37120 | 128.00 | 0.01 | 1.60 | -7.37 | 12.98 | 170455.64 |
| China | 1996/01/02 | 2020/02/01 | 124990 | 431.00 | 0.08 | 1.79 | -9.59 | 6.80 | 4238218.49 |
| Egypt | 1996/01/02 | 2020/02/01 | 20880 | 72.00 | 0.04 | 1.72 | -22.69 | 5.59 | 70080.30 |

| | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| India | 1996/01/02 | 2020/02/01 | 94250 | 325.00 | 0.12 | 2.01 | -12.61 | 14.57 | 1290405.09 |
| Indonesia | 1996/01/02 | 2020/02/01 | 55390 | 191.00 | 0.11 | 1.24 | -6.28 | 9.69 | 218738.54 |
| Malaysia | 1996/01/02 | 2020/02/01 | 75110 | 259.00 | 0.03 | 0.86 | -5.03 | 3.89 | 281881.58 |
| Mexico | 1996/01/02 | 2020/02/01 | 28420 | 98.00 | 0.06 | 1.50 | -14.24 | 7.04 | 292790.11 |
| Peru | 1996/01/02 | 2020/02/01 | 33060 | 114.00 | 0.02 | 0.60 | -8.61 | 10.70 | 52261.52 |
| Poland | 1996/01/02 | 2020/02/01 | 35090 | 121.00 | 0.08 | 1.74 | -10.65 | 4.72 | 108370.59 |
| South Africa | 1996/01/02 | 2020/02/01 | 59450 | 205.00 | 0.05 | 1.62 | -8.34 | 8.51 | 601824.84 |
| Thailand | 1996/01/02 | 2020/02/01 | 74240 | 256.00 | 0.05 | 0.68 | -4.09 | 2.43 | 214796.41 |
| Turkey | 1996/01/02 | 2020/02/01 | 69310 | 239.00 | 0.03 | 2.34 | -23.50 | 11.72 | 150949.10 |
| Developed Markets | | | | | | | | | |
| Australia | 1996/01/02 | 2020/02/01 | 89610 | 309.00 | -0.24 | 2.31 | -14.77 | 17.17 | 914361.98 |
| Austria | 1996/01/02 | 2020/02/01 | 17400 | 60.00 | 0.02 | 0.81 | -6.90 | 2.41 | 89693.72 |
| Belgium | 1996/01/02 | 2020/02/01 | 28420 | 98.00 | -0.03 | 1.19 | -10.39 | 4.54 | 268968.22 |
| Finland | 1996/01/02 | 2020/02/01 | 30160 | 104.00 | 0.01 | 1.18 | -6.95 | 4.81 | 179596.33 |
| France | 1996/01/02 | 2020/02/01 | 98890 | 341.00 | 0.01 | 0.70 | -3.48 | 2.85 | 1721013.77 |
| Norway | 1996/01/02 | 2020/02/01 | 30450 | 105.00 | -0.02 | 2.65 | -21.21 | 15.46 | 177392.79 |
| Portugal | 1996/01/02 | 2020/02/01 | 13050 | 45.00 | -0.01 | 1.33 | -7.82 | 9.49 | 67147.60 |
| Singapore | 1996/01/02 | 2020/02/01 | 71340 | 246.00 | 0.01 | 1.15 | -8.29 | 6.48 | 418675.06 |
| Spain | 1996/01/02 | 2020/02/01 | 33060 | 114.00 | -0.01 | 1.07 | -6.71 | 3.64 | 835566.44 |

Notes: Table three presents brief information about the countries included in this study. The period is between January 1996 to February 2020. The table details the number of firms with complete data over the period of study. A number of filters were used to account for microstructure problems associated with the developing equity sample. Only stocks with complete returns information in month $t$ and market cap records in month $t-1$ are considered in the sample. Market size, measured in US dollars, compares the depth and size of these markets. For developing and in some cases emerging countries, firms are included in the sample as data becomes available. For developed countries, because of less data challenge, only firms and countries with data as of January 1996 are included in the sample. The first observation indicates the date, especially for developing countries when the data became available, while the last observation is uniform to all the countries in the sample. Number of firm month Observation is calculated as the total number of firm times the number of months minus firms with missing data $(N \times T) - Missing\ Obs$), where $N$ is the total number of firms, and $T$ is the total number of months since the firm's first observation.

It should be emphasized that developing countries are included in the study as data becomes available. Besides, countries such as Kenya had few firms listed with complete data by 1992; however, the numbers increased by 1996, informing the decision to start the sample in January 1996. It is also worth pointing out that the sample chosen for comparative analysis of developed markets in the study is not frequently studied in most of the cross-country asset pricing research. Most asset pricing tests over the years have consistently used data from large markets such as Canada, UK, Japan, US, and Germany, leaving the sample of developed markets selected for this study largely untapped in asset pricing tests, especially in comparative analysis of international asset pricing data (see Fama and French, 2012, 2017; Lee, Ng, and Swaminathan, 2009; Stulz, 1981; Zhang, 2006; Hou et al., 2011; Chaieb et al., 2021). Moreover, some of the developed markets such as Spain and Portugal have relatively small market capitalizations. Market size makes for an interesting observation in Table **3**: of the 42 countries included, the 20 developing countries only account for about 3.38% of the total market cap. The 13 emerging markets account for the biggest chunk at 62.28%, while the 9 developed markets included in the study command 34.34% of the combined market capitalisation. Thus, emerging markets included in the study account for over half of total value of the firms in the study. This may be because countries such as China and India have reported significant growth in listing and in firm sizes over the period of the study, hence possibly inflating the total capitalization of firms in the emerging markets category of the sample. On the other hand, developed markets in the sample are small, relative to traditionally investigated developed markets. For instance, countries like Portugal and Austria have smaller markets compared to emerging markets like Brazil, Malaysia, Turkey, and South Africa, and even Sri Lanka, which is a developing equity market.

On average, developing equity markets full sample comprises of 5564.36 firms with complete data over the sample period. This represents about 27.1% of the total firms included in the

entire sample. Going by the standards set in influential asset pricing studies[14], this sample is large enough to permit comprehensive asset pricing tests. Emerging equity markets provide the bulk of the firms in the study, accounting for almost half of the total at 47.3% while developed equity markets represents about 25.6% of the firms in the study.

Examination of Table 3 reveals that firms in developing equity markets and emerging markets, to a large extent, produce the highest average returns compared to those in developed markets. For instance, over the period of this sample, Croatia offered up to 30.82% monthly returns. However, the attractive returns also come at a high risk, as the standard deviations of returns for developing equity markets are much larger than those of emerging and developed markets.

Extant finance literature reports that firms in developing equity markets display uneven distribution of firm size measured by market capitalization. Studies further disclose that few big firms account for a significant percentage of the total market capitalization, hence leading to highly skewed data when using firm size as a yardstick to sort the data. It is thus not surprising that most asset pricing studies in frontier and emerging markets implement 90% vs. 10% as the representation of small and big firms, respectively, when constructing portfolios based on firm characteristics (Fama and French, 2012; Zaremba and Maydybura, 2019). The preliminary observation on size in Table 3 further justifies using equal-weighting criteria in constructing developing equity markets test portfolios. This is consistent with established traditions in the literature, where value-weighted portfolios are often used alongside equal-weighted portfolios in empirical tests. Few examples in frontier markets include Zaremba et al. (2019), Blackburn and Cakici (2017), and De Groot et al. (2012).

[14] Seminal asset pricing studies include Fama and MacBeth (1973), Fama and French (2012), Fama and French (2015), Fama and French (1993), Chen et al. (1986), Amihud and Mendelson (1986a), Harvey and Liu (2018), Feng et al. (2020), Novy-Marx (2013), Harvey and Liu (2019) and Kozak et al. (2018) among others

## 4.3 **Description of Variables**

Given the plethora of factors identified in asset pricing tests, one needs to be careful while addressing the identity of factors or variables that can make the list in an empirical asset pricing test. This study is based on a procedural approach in identifying the most robust risk factors in developing equity markets. There is no pre-specification of the factors to price or test their ability to command a risk premium. However, although it may not be possible to go for all the risk factors documented in the literature, the study is guided by theory and recent methodical advances to settle on factors that can be reasonably included in our identification strategy. This approach finds justification in Fama and French (2018), who advise that only factors that are theoretically sound such as market beta, size, value, and profitability should be considered. It is also imperative on this study to keep the fundamental principle of parsimony in asset pricing.

Harvey, Liu, and Zhu (2016) categorize asset pricing risk factors into two. The first category described as common factors, because such factors proxy for common sources of risk and their risk exposures helps span patterns in the cross-section of returns. The second category is labelled as characteristics because they are specific to individual assets or portfolios. Pukthuanthong et al. (2018) on the other hand, distinguishes between two sets of asset pricing risks, those that command risk premiums as true risk factors and the ones that only move returns, but not associated with systematic return differences, as unpriced. Priced risk factors are based on fundamentals, while unpriced factors are purely based on characteristics. Pukthuanthong et al. (2018) also note that the non-priced risk factors are important because they offer investment opportunities to arbitrageurs.

Consequently, this study considers two sets of variables consisting of firm fundamental variables and macroeconomic variables. The firm characteristics variables consist of size (market capitalization), BM (Book-to-Market divided by Market Cap), Investment (Change in total Assets), OP (Operating profitability), DE (Debt equity ratio, or leverage), IML (Illiquid

minus liquid stocks; liquidity is defined as the change in volume of shares traded), MOM (Momentum), PMN (Persistence minus Non-persistence), and PMU (Predictable minus Unpredictable capitalization, book-to-market value while macroeconomic variables comprise of domestic and international/global. Table 5 provides detailed description of both domestic and global macroeconomic variables included in the study.

### 4.3.1 Description of Factors

Along with the widely investigated firm characteristics, we introduce two additional, non-traditional firm fundamental variables, namely, earnings persistence, and earnings predictability. Earnings is central to many economics, finance, and accounting concepts about firm's value. A good earnings record is expected to disseminate pertinent information about the health of the organization to stakeholders. Therefore, earnings are used by many investors as a critical component of their utility maximization function and a decision aid barometer to invest in a specific company. Earnings persistence, earnings volatility, and earnings predictability have generated intense debate in the finance literature. Studies such as Dichev and Tang (2009) investigate the relationship between earnings volatility and earnings predictability, while Cheng and Wu (2013) evaluates the effects of earnings persistence on earnings predictability. In both studies, authors contend that earning is a critical accounting indicator which signals health of a firm to the investors. They argue that earnings are superior to cashflows because earnings communicate and summarise finer details about a firm's financial position. Thus, in this study, the two variables are aimed at interrogating the impact of accounting quality on stock returns, and by extension, investor behaviour following the release of accounting information.

The quality of accounting information has been established to substantially impact on a company's financial position (see, e.g., Zhai and Wang (2016) for Chinese evidence) For developing countries, earnings as an indicator of a healthy firm may have implications for the

investors in many ways. First, it has been established that non adherence to globally recognised accounting standards in disclosing accounting information negatively impact earnings and investments in developing markets (García, Alejandro, Sáenz, and Sánchez, 2017). Yet, corporate governance, a critical component of Prudential Financial reporting practice, is underdeveloped in many developing economies. Consequently, application of globally recognised accounting and financial reporting standards generally fall short in many of these countries. In Tunisia, Houcine (2017) established that quality financial reporting significantly increase investment efficiency.

Empirically, the impact of earnings on stock returns has received considerable attention in finance research. For instance, Kormendi and Lipe (1987) are among the early researchers to investigate the reactions of unexpected earnings on stock return volatility. Kormendi and Lipe (1987) questioned whether a firm's reported earnings can signal the market about the firm's value. Building on the earlier hypothesis of Miller and Rock (1985) that the magnitude of a firm's return explained by innovations in earnings is a function of its earnings persistence, Kormendi and Lipe (1987) empirically established that earnings persistence portray a one-for-one relationships with stock returns. They both defined earnings persistence as the impact innovations in earnings have on future cashflows. Hence earnings persistence, as they opined is obtained from the slope coefficient in a regression model relating current earnings to past earnings. Their definition of earnings persistence was later applied in an empirical evaluation of accounting quality on earnings by Zicke and Kiy (2017) which we also favour for the current study. Gschwandtner and Hauser (2016) also found evidence linking earnings persistence to stock returns in the US: their results support a positive relationship between long-run profitability and stock returns.

The definition of earnings persistence and earnings predictability variables in this study follows the procedure of Zicke and Kiy (2017), who investigate the impact of accounting standards on

financial reporting in Germany. In our case, 'earnings' is defined as operating profitability, and to derive the two variables, we run a rolling linear regression of OP on its past values. Earnings persistence measures the extent to which current earnings will recur in future, while earnings predictability measures the extent to which past earnings numbers can explain current earnings. To determine earnings persistence and earnings predictability, we run a linear regression relating current earnings to one period lagged earnings values as shown in equation 22.

$$OP_{it} = \alpha_0 + \alpha_1 OP_{it-1} + v_{i,t} \tag{22}$$

where $OP_{it}$ is firm $i$'s current operating profitability, $\alpha_0$ is a constant, $\alpha_1$is the coefficient of firm $i$'s previous operating profitability, and $v_{i,t}$ is idiosyncratic values, or part of the current operating profitability unexplained by previous one-period operating profitability. The parameter, $\alpha_1$, captures the persistence in operating profitability, while $v_{i,t}$ captures the predictability of operating profit. Therefore, to obtain the two variables, we extract the coefficients of the regressor variable and the residuals series from the regression. We then use the extracted series as persistence and predictability variables, respectively. Given the ability of profitability factor as espoused by Novy-Marx and Velikov (2016), and Hou, Xue, and Zhang (2015) to influence and explain anomalies in stock returns, we find it imperative to further interrogate the ability of a firm's profitability in influencing investor behaviour and return variations. We do this by examining the historical influence of profitability as an important indicator for potential investor behaviour, and as well a significant component of stock return variability through predictability and persistence.

To secure the primary objective of this study, which is to identify factors and variables important for returns variations, and related to underlying systematic risk drivers, we construct factor portfolios in two tacks. The first track portfolios are constructed from individual country data. Individual country portfolio construction alongside domestic macroeconomic variables

are aimed at appraising country-specific characteristics important for stock price discovery mechanisms and return generating process unique to these countries. The implementation takes a simple $(2 \times 2)$ sorting in which stocks are divided into two size groups, small and big, using the median market cap of all the firms in the sample at country level.

The portfolios are rebalanced at the end of June each year following previous studies (Athanassakos and Schnabel, 1994; Li, Zhang, and Zheng, 2018). Yearly rebalancing of the portfolios accounts for delisting problem common in many less developed markets. Only stocks with returns data in month $t$ and capitalization data in month $t-1$ form the surviving sample. Further, studies have observed that strong January effects are a result of heightened investor activity towards the end of the year (Athanassakos, 1992; Athanassakos and Schnabel, 1994; Easterday and Sen, 2016; Zaremba and Umutlu, 2018). This may plausibly present significant implications for the portfolio rebalancing at year-end. Big stocks are the $90^{th}$ percentile market cap, while small stocks are the $10^{th}$ percentile market cap. The next groups sort stocks into two groups, where the first sorts are the stocks with $30^{th}$ percentile of the sorting variable, and the second is the $70^{th}$ percentile of the sorting variable, say book-to-market labelled as BM. The intersection between the size group and the second sorting variable produces two small second sorting variable and two big second sorting variable, respectively. Clarity about these procedures is detailed in Table 4, panel B.

Second, track portfolios are constructed from a pooled sample of all the developing equity markets. Because pooled sample creates a large pool of firms, portfolios in this track are more diversified compared to the first track. Instead of using the restrictive $(2 \times 2)$ sorting, here we implement the more frequently employed $(2 \times 3)$ sorting procedure[15]. Like the first track,

[15] The procedure follows the seminal asset pricing research of Fama and French (1993). Numerous studies have used this procedure in testing the factors proposed by Fama and French, and even go beyond to include other factors constructed using the same principle.

stocks are divided into two size groups using pooled market cap as small and big, respectively, where small stocks are the $10^{th}$ percentile of total pooled market cap, while big stocks are the $90^{th}$ percentile of the pooled market cap. The second sorting variables are divided into three categories of stocks, where the first sorts are the $30^{th}$ percentile, the second is the middle $40^{th}$ percentile, and the last is the $70^{th}$ (lower 30, middle 40, and last 30) percentiles. To ensure that all markets are represented in this second stage sorting, a stock is first categorized as large in its own market and remains large in the pool of markets.

The first factor constructed is the market factor (MKT)[16], which is the US dollar return on the pooled indices of all the sampled equity markets minus the U.S. one-month T-bill rate. To pool the market factor, we use the leading market index of a particular country weighted by the total market capitalization. The other factors are constructed using six value-weighted $(2 \times 3)$ portfolios formed on size (ME) and book-to-market (BM), six value-weighted portfolios formed on size and operating profitability, six value-weight portfolios formed on size and liquidity, six value-weighted portfolios formed on size and investment, six value-weighted portfolios formed on size and leverage, six capitalization-weighted portfolio formed on size and momentum, six capitalization-weighted portfolio formed on size and profit predictability, and six capitalization-weighted portfolio formed on size and profit persistence.

The second track of portfolios is only used upon determining factors strongly related to the covariance matrix of returns. There is no guarantee, however, that all the portfolios sorted on firm characteristics, as described in track one, will make it to the second phase of the study where an asset pricing test is conducted. Thus, we also perform the same procedure of factor identification for the pooled sample. This is because, at the country-level, each country may

[16] The Market factor here is considered domestic to developing equity markets, for global market, MSCI is considered. Except for the global factors, factors constructed on firm characteristics are specific to the regions, for instance market factor used in the pooled sample is specific (domestic) to developing equity markets, and so is the SMB, HML, IML, etc.

qualify different factors, whereas in some countries, possibly none. This would in turn make it difficult to identify factors to be included for the pooled test and, therefore, to conduct the pooled test.

Again, portfolio returns may behave differently in a group/pool than they do at the country-level. Consequently, our decision to advance a factor to the second stage of analysis is partly based on the average performance of the $(2 \times 2)$ portfolio sorts on the individual country data, and partly on the overall performance of the same factors in the pooled sample. Specifically, for the 20 countries included in the sample of developing equity markets, if say SMB and IML factors strongly correlate to the return covariance matrix of more than 10 countries and consequently passes the pooled sample identification, then the two factors form part of the factors to be considered for asset pricing tests in stage two of the study.

As we have already described, factors that survive factor identification stage are reconstructed using a pooled sample. And because pooled samples offer greater variability due to the larger set of firms in each pool, we adopt a more diversified criterion as already discussed in track two of factor construction and Table 4. This procedure is motivated from a statistical viewpoint rather than economic theory; however, it is not finality in itself; the constructed factors may as well fail the asset pricing tests. Furthermore, the second phase of this study employs a battery of competing methods that ensures the final asset pricing factors are the true risk drivers in the developing equity markets.

In addition to firm fundamental variables elaborated in the preceding paragraphs, this study also incorporates a group of domestic and global macroeconomic variables deemed systematic sources of stock return volatility. The variables are viewed as exogenously determined state variables with the ability to affect future cash flows, discount rates, and alter expected dividend payoffs. The choice to include them is also aligned with the fundamental question of market

integration. Stock markets across the world are inevitably susceptible to global macroeconomic news through international economic interdependences in the real economic sector, even when they may seem segmented or partially integrated with one another.

The macroeconomic variables considered in this study have been carefully selected as discussed in chapter 3 and, in some cases, lean on the seminal study of Chen et al. (1986), who theoretically motivate and empirically test the pervasive influence of macroeconomic factors. The variables identified and motivated by Chen et al. (1986) have since received numerous empirical attentions. For instance, Azeez and Yonezawa (2006) used the APT approach to investigate the influence of industrial production, money supply, inflation, and term structure on Japanese stock market. Shanken and Weinstein (2006) re-examined the Chen et al. (1986) five factors for the US market and only found one factor, the industrial production significantly priced in the US stocks. Elsewhere, Chen and Chiang (2016) investigated the impact dividend yields, turnover in trading volume, the macroeconomic climate, and Chinese yuan per US dollar exchange rate on stock returns and find evidence supporting the influence of these macroeconomic factors on securities pricing in China.

In frontier equity markets, empirical studies such as Adjasi (2009), Kyereboah-Coleman and Agyire-Tettey (2008), Bahloul, Mroua, and Naifar (2017), Suhaibu, Harvey, and Amidu (2017), are clearer cases that macroeconomic environment eminently affect risk-return trade-offs in developing equity markets. The studies, however, chiefly interrogate the impact of macroeconomic variables from the monetary policy standpoints, while giving little or no attention to the fiscal side of the macro-environment spectrum. The use of monetary policy based macroeconomic variables like money supply, interest rates, inflation rates feature prominently in the above studies compared to fiscal policy instruments like taxation, public expenditure, public debt, and national budgets. Other studies in frontier equity markets such as

Piljak (2013), Dewandaru, Masih, and Masih (2017), Balcilar et al. (2019) among others feature the impact of global factors on domestic stock returns in developing equity markets.

A deep dive into the above studies suggest that variables describing the political and governance environment of the researched countries are not modelled alongside the macroeconomic variables. Despite their significance on the business environment (Cule and Fulton, 2013), governance indicator variables have received little attention on their direct impact on securities returns in developing equity markets. Therefore, in this study, governance indicator variables are given the same platform as the macroeconomic indicator variables.

Elsewhere, studies are nonetheless increasingly incorporating governance indicator variables in asset pricing studies. For instance, Cao et al. (2019) establish that local corruption leads to stock price crash in China. Ahmed (2020) uses system GMM to explore the impact of corruption on equity market performance on a broad sample of Islamic and conventional equity markets in emerging and developed markets. Their results show that corruption exerts significant negative effects on conventional and Islamic stock returns alike. Ahmed (2020) further find that conventional and Islamic emerging countries markets are more susceptible to corruption than developed countries stock markets.

Sherif and Chen (2019) investigate the impact of governance quality variables; accountability, level of corruption, and governance effectiveness on momentum premiums in the international setting, and establish that quality of governance consistently affects international momentum profits. Nguyen et al. (2019) similarly employ system GMM to investigate the impact of institutional environment, government effectiveness, regulatory quality, rule of law, and control of corruption and produce evidence suggesting significant positive impact of the variables on stock return co-movements between a selected emerging and US stock markets.

Given the increased interest in testing of governance variables on stock returns, we include two of the widely investigated governance indicator variables, regulatory quality (REQ) and rule of law (ROL) in this study. Quality governance or simply institutional indicators are important for investment as they provide environment of trust where investors can reasonably project their investments (see, Carrieri et al., 2013). Peace of mind and certainty to investors has been found to encourage capital flows, increase stock market integration and generally improve capital market performance (Geleilate, Magnusson, Parente, and Alvarado-Vargas, 2016; Modugu and Dempere, 2020). Governance quality can be viewed as the rules in a society defined by the socio-economic environment for flawless interaction of human and economic activities. They are associated with reduced information asymmetry, reduced transaction cost, enhanced market efficiency which transparently encourage and improve asset allocation (Pinar and Volkan, 2018).

To define and derive the other macroeconomic factors, we largely adopt the procedures put forward by Chen et al. (1986) as already discussed. The global versions of the macroeconomic variables in this study are defined by the weighted averages of GDP per capita in U.S dollars. In computing unanticipated inflation (UI), we employ the procedure of Cooper, Mitrache, and Priestley (2019) who defines UI as $UI_t \equiv I_t - E[I_t|t-1]$ and change in expected inflation (DEI) as $DEI_t \equiv E[I_{t+1}|t] - E[I_t|t-1]$. Inflation $I_t$ is derived using changes in monthly CPI for each country as $I_t = logCPI_t - logCPI_{t-1}$. Expected inflation on the other hand is defined as $E[I_t|t-1] \equiv r_{f,t} - r_{i,t}|\ t-1$ where $r_{i,t}$ is the return on real interest rates, or realised earnings from 3-month treasury bill rate minus rate of inflation defined as $r_{i,t} = r_{f,t} - I_t$.

Other global macro variables constructed using the intuition of Chen et al. (1986), but with the insights of Cooper et al. (2019) include global term premium (GTP) and global default spread (GDS). Since country level and firm level data are not easily available to construct term premium and default spread at the domestic level, we construct these factors using global

measures, and include them as part of exogenous global macroeconomic factors. Global term premium GTP is therefore, defined as the spread between U.S GDP-weighted yield of ten-year bond and the one-year Treasury bonds yield. GDS is constructed using the yield spread between Moody's Baa and Aaa corporate bonds.

Aggregate volatility (VOL) is calculated from each country's stock market index using a simple GARCH (1,1) process similar to the one employed by Syriopoulos et al. (2015). Aggregate liquidity (LIQ) definition on the other hand relies on the principles outlined by Pástor and Stambaugh (2003), but with a slight modification. Specifically, our measure makes use of monthly stock returns, monthly trade volume, turnover and monthly aggregate stock returns.

Monetary theory relate money supply to aggregate economic activity[17]. In relation to influence on aggregate economic activities, a number of influential studies have documented a link between money supply and stock retruns across the world. In a recent example, Thanh et al. (2020), find that changes in money supply (monetary policy shocks) have a significant lagged impact on stock prices in India. Ouma and Muriu (2014) test the impact of money supply alongside three other macroeconomic variables on stock prices in Kenya and find significant evidence detailing that money supply has positive impact on stock returns in Nairobi Securities exchange. In this study, broad money supply (M2) is used alongside 17 other macroeconomic variables.

Other global macroeconomic variables included in the study are discussed and described in Chapter 3. They comprise of Agricultural commodity index (AGR), US consumer confidence (CC), IP industrial production index, return on composite metal index (MTL), Morgan Stanley

[17] Friedman and Schwartz (1963) trace US monetary policy for a period of 93 years (1867 to 1960) and establish that changes in the money supply profoundly influenced economic fluctuations in the US. The authors discovered that changes in money supply had unintended adverse economic consequences. Friedman and Schwartz (1963) make use of the Quantity Theory of Money (QTM) developed by Nicolaus Copernicus in 1517. Other notable empirical and theoretical attempts to relate money supply to stock prices include Homa and Jaffee (1971), Hamburger and Kochin (1972), Cooper (1974), Pesando (1974),

Capital international Index (MSCI), changes in brent crude oil prices (OIL), US trade weighted exchange rates (TW$) and 30-days S&P 500 options volatility index (VIX).

### 4.4 Descriptive statistics for firm characteristics and macroeconomic variables

Descriptive statistical analyses presented in this section are aimed at identifying macroeconomic and firm characteristics variables capable of influencing stock returns in developing equity markets. Put differently, attention is deliberately directed at determining macroeconomic variables and characteristic drivers of covariance matrix of returns in the sample of focus. To execute this, canonical correlation analysis[18] between the predetermined principal components of the demeaned returns of individual firms[19] is conducted against individual firm characteristics and the selected domestic and global macroeconomic variables. The results of this analysis highlight the ability of the selected macroeconomic variables and firm characteristics as candidate risk factors for subsequent empirical asset pricing tests. Furthermore, this part of the study explicates the preliminary behaviour of the candidate risk factors in each country, and reinforces the decision taken to include a particular risk factor or a set of risk factors in the empirical asset pricing test.

In addition to the developing equity markets, the focus of this study, we also present similar statistics for the 13 emerging markets and 9 developed markets in the pooled sample. We believe this provides significant latitude in gauging the behaviours of these factors and variables across the sampled markets.

[18] Canonical Correlation Analysis (CCA) maximises linear relationships between two sets of variables.
[19] In each country, PCA is conducted for monthly demeaned stock prices, and a maximum of 10 PCs are extracted. This number is predetermined to enable a uniform analysis of all the countries included in the sample. There is no specific scientific, mathematical, or statistical justification laid down for this decision.

Table 3**: Factor Construction**

| Sorts | Breakpoint | Factors and their components |
|---|---|---|
| Panel A: 2 × 3 sorts portfolio sorts (for pooled sample) | | |
| size and BM | Size: 90th and 10th percentiles | $SMB_{BM} = (SH + SN + SL)/3 - (BH + BN + BL)/3$ |
| size and Inv | | $SMB_{Inv} = (SC + SN + SW)/3 - (BC + BN + BW)/3$ |
| Size and OP | | $SMB_{OP} = (SR + SN + SA)/3 - (BR + BN + BA)/3$ |
| Size and DE | | $SMB_{DE} = (SH + SN + SL)/3 - (BH + BN + BL)/3$ |
| Size and Liq | | $SMB_{Liq} = (SI + SN + SL)/3 - (BI + BN + BL)/3$ |
| Size and Mom | | $SMB_{Mom} = (SD + SM + SU)/3 - (BD + BM + BU)/3$ |
| Size and PST | | $SMB_{PST} = (SP + SM + SN)/3 - (BP + BM + BN)/3$ |
| Size and PRD | | $SMB_{PRD} = (SP + SN + SU)/3 - (BP + BN + BU)/3$ |
| | | $SMB = (SMB_{BM} + SMB_{Inv} + SMB_{OP} + SMB_{DE} + SMB_{Liq} + SMB_{Mom} + SMB_{PST} + SMB_{PRD})/8$ |
| | Second sorting variable | |
| | BM:30th and 70th percentiles | $HML = (SH + BH)/2 - (SL + BL)/2$ |
| | Inv:30th and 70th percentile | $CMA = (SC + BC)/2 - (SA + BA)/2$ |
| | OP:30th and 70th percentile | $RMW = (SR + BR)/2 - (SW + BW)/2$ |
| | DE:30th and 70th percentile | $DE = (SL + BL)/2 - (SH + BL)/2$ |
| | Liq:30th and 70th percentile | $IML = (SI + BI)/2 - (SL + BL)/2$ |
| | Mom:30th and 70th percentile | $UMD = (SU + BU)/2 - (SD + BD)/2$ |
| | PST: 30th and 70th percentile | $PMN = (SP + BP)/2 - (SN + BN)/2$ |
| | PRD: 30th and 70th percentile | $PMU = (SP + BP)/2 - (SU + BU)/2$ |
| Panel B: 2 × 2 portfolio sorts (for individual country sample) | | |
| | Size: Median Market Cap | |
| size and BM | BM:30th and 70th percentiles | $HML = (SH + BH)/2 - (SL + BL)/2$ |
| size and Inv | Inv:30th and 70th percentile | $CMA = (SC + BC)/2 - (SA + BA)/2$ |
| Size and OP | OP:30th and 70th percentile | $RMW = (SR + BR)/2 - (SW + BW)/2$ |
| Size and DE | DE:30th and 70th percentile | $DE = (SL + BL)/2 - (SH + BH)/2$ |
| Size and Liq | Liq:30th and 70th percentile | $IML = (SI + BI)/2 - (SL + BL)/2$ |
| Size and Mom | Mom:30th and 70th percentile | $UMD = (SU + BU)/2 - (SD + BD)/2$ |
| Size and PST | PST: 30th and 70th percentile | $PMN = (SP + BP)/2 - (SN + BN)/2$ |
| Size and PRD | PRD: 30th and 70th percentile | $PMU = (SP + BP)/2 - (SU + BU)/2$ |

$$SMB = (SH + SL + SC + SA + SW + SR + SW + SL + SH + SI + SL + SU + SD + SP + SN + SP + SU)/17 - (BH + BL + BC + BA + BR + BW + BL + BH + BI + BL + BU + BD + BP + BN + BP + BU)/17$$

This table details the criteria used in constructing asset pricing factors in developing equity markets. Panel A portfolios are constructed using six value-weight (2×3) portfolios formed on pooled size (ME) and book-to-market (BM), six value-weight portfolios formed on size and gross profitability, six value-weight portfolios formed on size and liquidity, six value-weight portfolios formed on size and investment, six value-weight portfolios formed on size and leverage, six value weight portfolios formed on size and momentum. To construct the SMB, HML, RMW, IML, CMA, DE, PMN and PMU factors, pooled stocks are divided into two market cap (ME, 90%:10%) groups and three groups for the respective firm characteristic. These include three groups for the book-to-market equity (BM), Operating Profitability (OP), Liquidity (LIQ), investment (INV), Leverage (DE), Momentum (MOM), Persistence (PST), and Predictability (PRD) groups at the end of each June. SMB, size factor (Small Minus Big) is the average return on the twenty-seven small stock portfolios minus the average return on the twenty-seven big stock portfolios. HML factor is constructed as the difference between average diversified returns of two high size-BM portfolios and two low size-BM portfolios as $(SH + BH)/2 - (SL + BL)/2$. Factors based on INV, OP, LIQ, DE and MOM are constructed in the same way as BM factors. CMA, investment factor is constructed using the difference between diversified portfolio returns of conservative firms minus diversified portfolios returns of aggressive firms $(SC + BC)/2 - (SA + BA)/2$. RMW is defined using the difference between diversified portfolios of robust operating profitability firms and weak operating profitability firms (SR+BR)/2-(SW+BW)/2. DE, the leverage factor is the average diversified portfolio returns of two size highly levered firms minus the average diversified portfolio returns of the two low levered firms $(SH + BH)/2 - (SL + BL)/2$. IML, the liquidity factor, is the average of diversified portfolio returns of the small and big illiquid firms minus the average diversified portfolio returns of small and big liquid firms $(SI + BI)/2 - (SL + BL)/2$. Momentum factor, UMD (up minus down) is constructed using the procedure provided by Skočir and Lončarski (2018a). Portfolios are formed at the end of month $t-1$, where the lagged momentum return is cumulative return of stock $i$ for month $t-12$ to month $t-2$. The momentum breakpoints for each are the bottom 30% (losers, D), middle 40% (Middle, M), and top 30% (Winners, U) of the lagged momentum return in the two size groups of the pooled sample. The independent (2×3) sorts on size and momentum produce six value-weight portfolios, SD, SM, SU, BD, BM, and BU, where S and B represent the small and big size stocks, and D, M, and U represent down, middle, and up respectively (bottom 30%, middle 40%, and top 30%). UMD is the equal-weight average of the returns for the two up portfolios for pooled markets minus the average of the returns for the two down portfolios. PMN, the persistence factor is constructed using the difference between diversified portfolio returns of firms with persistent operating profitability minus diversified portfolios returns of nonpersistent profitability firms $(SP + BP)/2 - (SN + BN)/2$. PMU, predictability factor is constructed using the difference between diversified portfolio returns of firms with predictable operating profitability minus diversified portfolios returns of unpredictable operating profitability firms $(SP + BP)/2 - (SU + BU)/2$. Panel B portfolios are constricted using four value-weigh $(2 \times 2)$ portfolios also formed on two size (ME) groups (S and B). Stocks are divided into small (S) and big (B) stocks using the individual country median market capitalization (ME) and two groups of the second sorting variables such as BM, INV, OP and the rest as described in Panel A. SMB construction in the $(2 \times 2)$ sorts (Small Minus Big) is the average return on the eighteen small stock portfolios minus the average return on the eighteen big stock portfolios.

**Table 4: Description of Domestic and Global Macroeconomic Variables**

| Variable Name | Literature Source | Factor Description | Factor Abbreviation |
|---|---|---|---|
| Expected Inflation | Chen et al. (1986) | Change in expected inflation. Expected inflation is the difference between return on real interest rates or realised earnings from 3-month treasury bill rate and rate of inflation. $DEI_t$=$r_{f,t} - r_{i,t}\mid\ t-1$ and $r_{i,t} = r_{f,t} - I_t$. $r_{f,t}$ is the real interest rates, $r_{i,t}$is the real return on treasury bills. | DEI |
| Unanticipated Inflation | Chen et al. (1986) | The difference between realised inflation and expected inflation | UI |
| Aggregate Liquidity | Pástor and Stambaugh (2003) | The cross-sectional monthly average of individual-stock liquidity in a country weighted by the average GDP per capita in U.S dollars | LIQ |
| Regulatory Quality | Nguyen, Nguyen, and Schinckus (2019) | According to World Bank Governance Indicators, "Regulatory Quality captures perceptions of the ability of the government to formulate and implement sound policies and regulations that permit and promote private sector development…" | REQ |
| Rule of Law | Nguyen et al. (2019) | Rule of Law captures perceptions of the extent to which agents have confidence in and abide by the rules of society, and in particular the quality of contract enforcement, property rights, the police, and the courts, as well as the likelihood of crime and violence. | ROL |

| | | | |
|---|---|---|---|
| Broad Market Volatility | Syriopoulos, Makram, and Boubaker (2015) | Calculated from each country's stock market index returns or leading index using GARCH (11) process. | VOL |
| Money Supply (M2) | Abbas, Hammoudeh, Shahzad, Wang, and Wei (2019) | Change in M2 money supply | MS |
| Agricultural Commodity Index | Baldi, Peri, and Vandone (2016) | SandP Agriculture; benchmark for performance in the global agriculture commodity market | AGR |
| US. Consumer Confidence Index | Bildirici and Badur (2019) | A survey of U.S consumers' opinions on current conditions and future expectations of the economy. | CC |
| Global Term Premium | Chen et al. (1986) and Cooper, Mitrache, and Priestley (2019) | The spread between U.S GDP-weighted yield of ten-year bond and the one-year Treasury bonds yield | GTP |
| Global default Spread | Chen et al. (1986) and Cooper et al. (2019) | The yield spread between Moody's Baa and Aaa corporate bonds | GDS |
| Metal Index | (Jordan, Vivian, and Wohar, 2016, 2018) | Industrial metals trading data from London Metal Exchange. | MTL |
| Global Stock Index (MSCI) | Al Nasser and Hajilee (2016) | MSCI index is used to mimic global stock market index. The index is used to evaluate the integration and co-movement of the markets investigated with the global markets | GI |
| Crude Oil Prices | Bildirici and Badur (2019) and Bai and Koong (2018) | Closing prices of brent crude oil (in Dollar per Barrel) on the New York Mercantile Exchange (NYMEX) | OIL |
| US $ Trade Weighted Exchange Rates | Bai and Koong (2018) | Measure trading activities between US and some of countries included in this study. According to Thomson Reuters DataStream (the source); "The other important trading partners (OITP) index is a weighted average of the foreign exchange values of the U.S. dollar against a subset of currencies in the broad index that do not circulate widely outside the country of | TW$ |

| | | | |
|---|---|---|---|
| | | issue. The index weights, which change over time, are derived from U.S. export shares and from U.S. and foreign import shares. Currencies included in the OITP index are Mexican peso, Chinese yuan, New Taiwanese dollar, Korean won, Singapore dollar, Hong Kong dollar, Malaysian ringgit, Brazilian real, Thai baht, Philippine peso, Indonesian rupiah, Indian rupee, Israeli new shekel, Saudi riyal, Russian ruble, Argentine austral, Venezuelan bolivar, Chilean peso and Colombian peso" | |
| SandP Volatility Index (VIX) | Qadan, Kliger, and Chen (2019) | The aggregate global market volatility risk proxied by the VIX index. The Index is calculated by the Chicago Board Options Exchange (CBOE) | VX |

**Table 5: Summary statistics for factors on accounting and macroeconomic variables**

| | Developing Markets | | | | | | Emerging Markets | | | | | | Developed Markets | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Mean | SD | Skew | Kurt | JB | P-Value | Mean | SD | Skew | Kurt | JB | P-Value | Mean | SD | Skew | Kurt | JB | P-Value |
| MKT | 0.18 | 5.94 | -0.48 | 5.12 | 48.70 | 0.01 | 0.24 | 2.93 | -0.21 | 3.84 | 21.53 | 0.00 | 0.53 | 2.95 | 0.28 | 5.18 | 29.06 | 0.01 |
| SMB | 0.33 | 3.75 | -1.49 | 9.22 | 34.37 | 0.04 | 0.15 | 1.63 | -1.11 | 6.92 | 18.28 | 0.00 | 0.21 | 2.20 | -1.50 | 9.34 | 24.67 | 0.00 |
| HML | 0.78 | 3.19 | 0.00 | 1.80 | 71.71 | 0.01 | 0.81 | 1.63 | 0.00 | 1.35 | 53.78 | 0.00 | 1.09 | 2.20 | 0.00 | 1.82 | 72.61 | 0.01 |
| CMA | -0.31 | 4.87 | -0.47 | 4.07 | 122.98 | 0.01 | -0.42 | 5.90 | -0.35 | 3.05 | 92.23 | 0.01 | 0.56 | 3.92 | -0.48 | 4.12 | 24.52 | 0.02 |
| RMW | 1.17 | 5.31 | 0.33 | 2.85 | 137.07 | 0.02 | 1.07 | 3.23 | 0.25 | 2.14 | 177.80 | 0.02 | 0.65 | 2.36 | 0.34 | 2.89 | 94.03 | 0.02 |
| DE | 0.29 | 3.15 | -0.16 | 5.93 | 93.32 | 0.03 | 0.39 | 2.36 | -0.12 | 4.45 | 69.99 | 0.03 | 0.53 | 3.19 | -0.17 | 6.01 | 94.48 | 0.03 |
| IML | -0.27 | 5.14 | 0.55 | 2.19 | 56.17 | 0.04 | 0.15 | 3.86 | 0.41 | 1.64 | 34.63 | 0.03 | 0.20 | 5.20 | 0.55 | 2.22 | 46.75 | 0.00 |
| UMD | 1.34 | 6.28 | -1.34 | 5.88 | 67.53 | 0.05 | 1.22 | 1.71 | -1.00 | 4.41 | 50.65 | 0.04 | 1.64 | 2.31 | -1.35 | 5.95 | 68.37 | 0.00 |
| PMU | 0.76 | 3.10 | -0.59 | 5.06 | 69.84 | 0.06 | -0.62 | 1.58 | -0.44 | 3.80 | 52.38 | 0.05 | -0.29 | 2.13 | -0.60 | 5.13 | 70.71 | 0.01 |
| PMN | 0.94 | 4.16 | -1.08 | 5.94 | 72.15 | 0.07 | 0.46 | 1.62 | 0.81 | 4.45 | 54.11 | 0.05 | 0.22 | 2.19 | -1.10 | 6.01 | 73.05 | 0.07 |
| DEI | -0.10 | 5.94 | -0.67 | 4.26 | 74.47 | 0.01 | -0.14 | 1.46 | -0.50 | 3.20 | 55.85 | 0.01 | -0.18 | 1.96 | -0.68 | 4.32 | 75.40 | 0.01 |
| UI | 1.38 | 2.78 | -0.46 | 6.08 | 76.78 | 0.00 | 0.89 | 2.09 | -0.34 | 4.56 | 57.58 | 0.00 | 1.20 | 2.81 | -0.46 | 6.15 | 77.74 | 0.00 |
| LIQ | 0.31 | 1.73 | -0.20 | 3.12 | 79.09 | 0.01 | 0.30 | 1.30 | -0.15 | 2.34 | 59.32 | 0.01 | 0.40 | 1.75 | -0.20 | 3.15 | 80.08 | 0.01 |
| REQ | 0.19 | 4.20 | -0.11 | 4.20 | 81.40 | 0.00 | 0.19 | 0.15 | -0.08 | 3.15 | 61.05 | 0.00 | 0.26 | 0.20 | -0.11 | 4.25 | 82.42 | 0.00 |
| ROL | 0.13 | 3.35 | -0.75 | 13.76 | 83.72 | 0.08 | 0.26 | 0.26 | -0.56 | 10.32 | 62.79 | 0.06 | 0.35 | 0.35 | -0.76 | 13.93 | 84.76 | 0.08 |
| VOL | -0.92 | 2.86 | 0.24 | 10.63 | 86.03 | 0.03 | -0.84 | 2.15 | 0.18 | 7.97 | 64.52 | 0.02 | -1.13 | 2.90 | 0.25 | 10.76 | 87.10 | 0.03 |
| MS | 0.15 | 3.15 | -2.13 | 12.09 | 88.34 | 0.06 | 0.15 | 0.11 | -1.60 | 9.07 | 66.26 | 0.04 | 0.20 | 0.15 | -2.16 | 12.24 | 89.44 | 0.06 |
| AGR | 0.96 | 2.96 | -0.59 | 5.07 | 90.65 | 0.00 | 0.96 | 2.96 | -0.59 | 5.07 | 90.65 | 0.00 | 0.96 | 2.96 | -0.59 | 5.07 | 90.65 | 0.00 |
| UCC | 0.26 | 0.21 | -0.67 | 2.88 | 92.97 | 0.00 | 0.26 | 0.21 | -0.67 | 2.88 | 92.97 | 0.00 | 0.26 | 0.21 | -0.67 | 2.88 | 92.97 | 0.00 |
| GTP | -0.17 | 2.99 | 0.74 | 5.04 | 95.28 | 0.01 | -0.17 | 2.99 | 0.74 | 5.04 | 95.28 | 0.01 | -0.17 | 2.99 | 0.74 | 5.04 | 95.28 | 0.01 |
| GDS | -0.26 | 4.63 | -0.82 | 3.72 | 97.59 | 0.01 | -0.26 | 4.63 | -0.82 | 3.72 | 97.59 | 0.01 | -0.26 | 4.63 | -0.82 | 3.72 | 97.59 | 0.01 |
| MTL | -0.29 | 0.07 | -0.89 | 2.26 | 99.90 | 0.01 | -0.29 | 0.07 | -0.89 | 2.26 | 99.90 | 0.01 | -0.29 | 0.07 | -0.89 | 2.26 | 99.90 | 0.01 |
| GI | 0.11 | 0.17 | -0.97 | 4.26 | 102.22 | 0.00 | 0.11 | 0.17 | -0.97 | 4.26 | 102.22 | 0.00 | 0.11 | 0.17 | -0.97 | 4.26 | 102.22 | 0.00 |
| OIL | 0.85 | 2.15 | -0.43 | 1.89 | 104.53 | 0.00 | 0.85 | 2.15 | -0.43 | 1.89 | 104.53 | 0.00 | 0.85 | 2.15 | -0.43 | 1.89 | 104.53 | 0.00 |
| TW$ | 0.06 | 3.49 | -0.12 | 3.98 | 106.84 | 0.00 | 0.06 | 3.49 | -0.12 | 3.98 | 106.84 | 0.00 | 0.06 | 3.49 | -0.12 | 3.98 | 106.84 | 0.00 |
| VX | -0.11 | 0.32 | -0.19 | 2.82 | 109.15 | 0.00 | -0.11 | 0.32 | -0.19 | 2.82 | 109.15 | 0.00 | -0.11 | 0.32 | -0.19 | 2.82 | 109.15 | 0.00 |

Notes: Table 6 presents results of descriptive statistical analysis for monthly (1996 M01 to 2020 M02) firm characteristic variables sorted on $(2 \times 3)$ and macroeconomic variables, domestic and international. Descriptive include mean return, maximum returns (max, minimum returns (min), standard deviation of the returns (SD) and skewness (Skew). MKT is the pooled market returns of all the countries less one-month US Treasury bill rate. At the end of each year

(June), stocks are allocated into two size groups using $90^{th}$ and $10^{th}$ percentiles to represent big (B) and small (S) stocks, respectively. Stocks are further assigned independently to three book-to-market equity (BM), investment (Inv), operating profitability (OP), Liquidity (LIQ), Momentum (MOM), predictability (PRD) and persistence (PRD) groups, using 30th and 70th percentiles of individual country stocks. HML are the portfolios formed from the intersection of the Size and BM sorts ($2 \times 3$), investment, profitability, leverage, liquidity, momentum, predictability, and persistence factors, CMA, RMW, ROA, IML, UMD, PMU and PMN, use six value weight portfolios from the intersection of the Size and the subsequent characteristic sorts. SMB, size factor (Small Minus Big) is the average return on the twenty-four small stock portfolios minus the average return on the twenty-four big stock portfolios. Domestic macroeconomic variables are DEI (changes in expected inflation), UI (unanticipated inflation), LIQ (aggregate liquidity), REQ (regulatory quality) ROL (rule of law), VOL (returns volatility), and MS (broad money supply, M2). Global macroeconomic variables include AGRIC (agricultural commodity index), CC (US Consumer confidence), GTP (changes in global term premium), GDS (changes in global default spread), Metal (return on composite metal index), GI (excess return of Morgen Stanley Capital International Index), OIL (return on crude oil prices), TW$ (US dollar broad trade-weighted exchange Index), VIX (US volatility index). P-value is the p-value of the Jarque-Bera (JB) statistic.

### 4.4.1 Summary Statistics

Table **6** details basic features of the explanatory variables included in this study. For the purposes of comparison, pooled sample is employed for the three market categories in the sample. As already highlighted in the preceding sections, there are two categories of variables (factors) presented in the table, the first category consists of firm-level factors constructed from accounting information variables and momentum, while the second category is the macroeconomic variables which are further classified into two, domestic and international. To conform to the standard empirical asset pricing tests, factors are constructed using a $(2 \times 3)$ sorting criterion. Market capitalization is used to divide the firms with available information into big and small, resulting into two size groups. Subsequent factors are constructed using $30^{th}$ and $70^{th}$ percentile, respectively of the second sorting variable. The intersection between the size groups and the subsequent variables produces small-low ($30^{th}$ percentile) and big-high ($70^{th}$ percentile). Detailed descriptions of these procedures have been discussed in the previous subsection of this chapter, as well as displayed in Table 4.

Country information (data), especially constructed portfolios, are included when the data become available. Our observation reveals that most accounting data for developing countries begin to have consistency in reporting and complete data from the year 2001, with some countries like Jordan, Nigeria, and Mauritius only reporting complete and consistent data on firm characteristic variables as from 2006, 2007, and 2009, respectively[20]. Nonetheless, these countries are still included in the analysis, and construction of their firm-level factors follows a procedure proposed by Berger et al. (2011) and discussed in the previous section. The

[20] Despite the missing firm-level accounting data at the inception of the sample, countries are still included in the sample so long as they have consistent stock price data. Nigeria for instance has stock price data from 2001, while firm fundamental data as from 2007. In their case, and as for other countries as well, we use the median value of all the countries in the same category with data on the missing sorting variable to construct the portfolios of these countries. Therefore, the short sample period displayed by Nigeria, Mauritius, and Jordan do not significantly impede on the implementation of the proposed empirical strategy.

procedure allows for setting a given country's sorting variable, say size equal to the median size value of all developing countries within the sample at that point in time. When the data becomes consistent, the system reverts to sorting using specific country information.

It is worth acknowledging a potential impact of time differences that exists among the sampled markets on arbitrage trading. According to Barberis, Shleifer, and Wurgler (2005), in investors may attempt to exploit the arbitrage opportunity created by time differences that exists in between the opening and closing for stock exchanges across the markets. This phenomenon however is prevalent when dealing with daily returns, and at most weekly returns, but may not be of a serious concern for our data which are observed on monthly frequency. By the end of the month, any arbitrage opportunity caused by time differences will have been averaged out (Birru, 2018; Jaffe and Westerfield, 1985).

Summary statistics displayed in Table 6 employ four major statistical moments to analyse the distribution properties of the regressor variables selected for this study. The moments include mean, standard deviation, skewness, and kurtosis. Jarque-Bera statistics and the accompanying p-values are used to evaluate the normality of the distributions. Inspection of the results indicates that the Mean values of UMD and RMW yield the highest average returns among the factors constructed on momentum and firm characteristics at 1.34% and 1.17% average returns per month, respectively. Other factors constructed on profitability variable seems to suggest the same trend as RMW. For instance, PMU and PMN, respectively, yield 0.76% and 0.94% monthly returns over the sample period. The HML factor[21] also present higher positive monthly average returns over the sample period at 0.78%. Market factor (MKT), size factor (SMB), and leverage factor (DE) all produce a positive average monthly return, albeit lower than the other

[21] Studies in less developed markets have consistently found HML factor highly pronounced in returns compared to SMB, RMW and even market factor. This so-called irregularity is associated with data problems often ubiquitous in such markets. It has also been alleged that the presence of many growth firms in these countries potentially contribute the significant presence of HML factor in their return generating calculus (Cakici et al., 2013; Nartea, Kong, & Wu, 2017; Shum & Tang, 2005).

factors. Liquidity (IML) and investment are the only factors producing negative average returns throughout the study period.

Emerging markets generally portray the same picture in terms of statistical summaries of factors constructed on firm characteristics. Like in developing equity markets, profitability, momentum, and book-to-market factors manifest the highest positive average returns in emerging markets. However, market return factors seem to portray a somewhat different picture in emerging and developed markets. Even though their average returns are positive, they seem to attract higher averages for the two markets compared to developing markets. CMA factor also joins this list of contrasts, as it yields negative returns in developing and emerging markets but seems to perform highly and positively in developed markets. Another noticeable contrast to developing and emerging markets is about factors constructed on gross profitability. Although the average returns of RMW is positive and comparatively high at 0.65%, its performance in the other two categories are way better for the period of the study. Earnings predictability factor has negative average returns for both emerging and developed markets in the study.

The contrasts revealed by Table 6 is not new for studies undertaking asset pricing studies investigating factors constructed on firm characteristics. Studies have repeatedly reported that factors associated with market frictions tend to manifest themselves strongly in emerging and frontier equity markets. For instance, Zaremba and Czapkiewicz (2017) document that factors mimicking market inefficiency or market friction outperforms the other factors constructed from firm fundamental variables. Cakici et al. (2013) also present evidence suggesting significant influence of value factor in describing equity returns in emerging equity markets.

Comparably, the domestic macro variables in developing equity markets manifest lower average returns, except for the unanticipated inflation (UI), which seems to yield the highest

monthly average returns, higher than some of the factors formed on firm characteristics. Other positive average returns among the domestic macroeconomic variables over the sample period include aggregate market liquidity (LIQ) at 0.31%, regulatory quality (REQ) at 0.19%, money supply at 0.15%, and rule of law (ROL) at 0.13%. Change in expected inflation (DEI) produces negative monthly average returns for the period of the study at -0.10%. Comparatively, market volatility portrays downside returns with a monthly average of -0.92%.

Within the global macroeconomic variables in the developing equity markets, agricultural commodities index (AGR) outperforms many of its counterparts in the study, with a mean return of 0.96%. It has been reported empirically that many of the markets in the developing equity markets to a large extent rely on agricultural produce as a significant financier of the national budgets, and hence a cornerstone of their overall macroeconomic performance.

As regards to statistical distribution properties, the variables, presented in Table 5, point to data with nonnormal distributions. Symmetric deviations from the mean ordinarily result in zero skewness. Values presented in Table 6 such as standard deviation, skewness, and kurtosis all points to asymmetric distribution. Using skewness (Skew), for example, suggests that market factor is negatively skewed in developing and emerging markets, but positively skewed in developed markets. While the skewness values for the three markets do not vindicate the factor in terms of symmetry, they do not look far apart either, or much closer to the canonical skewness coefficient of 0 compared to the other variables.

Closer scrutiny reveals that most of the variables are negatively skewed, and macro variables, both domestic and global have the highest negative average returns distribution compared to the local firm-specific variables. Coefficients of kurtosis also support non-normality in the data, since most of the coefficients are above 3, indicating a heavy-tailed distribution.

### 4.4.2 Correlation Analysis

Correlation analysis provides a brief description of the relationships between the candidate risk factors. Table 7 presents results of Pearson correlation analysis between pairs of the independent candidate variables. Except in few cases, results in Table 6 largely suggest that there is no strong linear relationship between pairs of the candidate variables. Strong relationships exist between momentum factor UMD and market factor MKT at 0.79, between momentum and profitability factor (RMW) at 0.75, between global default spread (GDS) and rule of law ROL) at 0.71, between global market return index (GI) and agricultural commodity index at -0.85, and between volatility index (VIX) and US consumer confidence (UCC) at 0.77. These variables may be exposing analogous dynamics, and hence can act as substitutes of each other, except for global returns index and agricultural commodity index which show a lockstep movement, but in different directions.

In Table 7, the market factor (MKT) produces significant correlation coefficient with a number of the regressor variables included in the study. However, of special interest is the relationship between the variables and the firm-level liquidity factor (IML) at -0.71 ($t$-stat>2.0),[22] and the aggregate liquidity factor (LIQ) at 0.73. The negative association between market factor and firm level liquidity factor is consistent with the implications of asset pricing theory (Amihud, 2002; Amihud and Mendelson, 1986b). In an empirical evaluation of an eight-factor model that includes the liquidity factor (IML), Skočir and Lončarski (2018) find negative and significant relationship between different sorts of liquidity and market factors. Consistent with their findings, liquidity and market factor relationship reported in Table 6 is among the highest significant correlations reported in the table the highest and significant of all the factors included in the analysis.

[22] Because of space constraints, the t-statistics are not reported. However, the table indicates, in bold, correlation coefficients with t-statistics greater than 2.0.

A closer observation across the table indicates that domestic and global variables in this study yield significant relationships, although with varying signs of the directions of correlation. This is an encouraging early sign of similar underlying drivers for the innovations in these data series, a possibility that domestic market variables are intricately related to the global macroeconomic environment. This is very encouraging for this study, given that the inclusion of the global variables alongside the domestic variables is specifically aimed at testing the integration hypothesis. Global variables such as agricultural commodity index, global default spread, consumer confidence, oil prices, US trade-weighted exchange rates, (US$) and volatility index (VIX), are significantly and strongly related to at least 10 of the domestic variables/factors. Given that we assume the position of the global investor in the study, the omission of domestic currency fluctuations as a candidate macro variable, and the resultant significance of the US trade-weighted exchange rates which measures trading activities between US and the markets included in this study, goes a long way in filling the gap of domestic trading activities ordinarily postulated to be captured by the exchange rates variable.

Table 6**:Correlation Analysis**

| | MKT | SMB | HML | CMA | RMW | DE | IML | UMD | PMU | PMN | DEI | UI | LIQ | REQ | ROL | VOL | MS | AGR | CC | GTP | GDS | MTL | GI | OIL | TW$ |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| SMB | **-0.31** | | | | | | | | | | | | | | | | | | | | | | | | |
| HML | **-0.42** | **0.66** | | | | | | | | | | | | | | | | | | | | | | | |
| CMA | -0.07 | **0.51** | 0.21 | | | | | | | | | | | | | | | | | | | | | | |
| RMW | **0.32** | 0.13 | **0.49** | 0.25 | | | | | | | | | | | | | | | | | | | | | |
| DE | -0.14 | 0.25 | 0.32 | -0.40 | -0.64 | | | | | | | | | | | | | | | | | | | | |
| IML | **-0.71** | **-0.60** | **-0.45** | **-0.48** | **-0.73** | **0.60** | | | | | | | | | | | | | | | | | | | |
| UMD | **0.79** | **-0.51** | **0.71** | **0.39** | **0.75** | **0.48** | **-0.31** | | | | | | | | | | | | | | | | | | |
| PMU | -0.12 | **-0.14** | **0.21** | -0.19 | -0.14 | 0.02 | -0.25 | **0.64** | | | | | | | | | | | | | | | | | |
| PMN | **-0.15** | -0.25 | -0.25 | -0.31 | -0.14 | **0.41** | -0.18 | **0.66** | 0.09 | | | | | | | | | | | | | | | | |
| DEI | **0.65** | -0.05 | **0.33** | -0.21 | **-0.59** | -0.05 | **-0.62** | **0.52** | 0.07 | -0.26 | | | | | | | | | | | | | | | |
| UI | **-0.54** | -0.07 | **-0.20** | 0.06 | **-0.46** | 0.05 | **0.65** | **-0.58** | **-0.54** | **-0.32** | **0.61** | | | | | | | | | | | | | | |
| LIQ | **0.73** | **-0.15** | **-0.27** | -0.13 | **-0.53** | 0.11 | **0.55** | **-0.46** | **0.27** | **-0.44** | -0.08 | **0.53** | | | | | | | | | | | | | |
| REQ | -0.18 | 0.03 | -0.24 | -0.07 | -0.16 | -0.10 | -0.15 | -0.07 | -0.14 | -0.11 | 0.10 | 0.20 | 0.43 | | | | | | | | | | | | |
| ROL | -0.48 | 0.35 | 0.14 | 0.27 | 0.05 | **-0.46** | 0.04 | -0.14 | **-0.67** | -0.09 | 0.37 | -0.06 | 0.26 | 0.27 | | | | | | | | | | | |
| VOL | **-0.61** | 0.23 | **0.64** | 0.13 | **-0.62** | **-0.24** | **-0.62** | **-0.66** | -0.30 | 0.08 | 0.08 | **-0.28** | **-0.60** | 0.24 | 0.16 | | | | | | | | | | |
| MS | **0.62** | 0.20 | 0.36 | -0.03 | -0.16 | -0.14 | -0.14 | -0.23 | -0.15 | 0.03 | 0.16 | **-0.26** | -0.25 | -0.03 | 0.12 | 0.13 | | | | | | | | | |
| AGR | **0.58** | 0.02 | **0.09** | 0.14 | **0.42** | -0.02 | **0.61** | **-0.57** | **-0.41** | **0.15** | **0.30** | **0.49** | **-0.54** | 0.25 | 0.38 | **0.53** | -0.29 | | | | | | | | |
| UCC | -0.09 | 0.01 | 0.07 | **-0.16** | **-0.58** | 0.43 | **-0.66** | **0.65** | **0.44** | **0.24** | **-0.49** | **-0.18** | **-0.63** | -0.11 | -0.31 | **-0.42** | **-0.49** | **0.73** | | | | | | | |
| GTP | 0.17 | **0.55** | **-0.55** | -0.07 | **0.45** | 0.13 | **-0.64** | **0.31** | **0.45** | **0.27** | -0.39 | -0.14 | **-0.21** | -0.24 | -0.46 | **-0.41** | -0.02 | **-0.26** | **-0.20** | | | | | | |
| GDS | **-0.43** | **-0.21** | **-0.54** | -0.09 | **0.64** | 0.20 | **0.59** | **0.24** | **0.61** | **0.33** | **-0.50** | -0.18 | **-0.23** | -0.32 | **0.71** | **-0.30** | **-0.45** | **-0.66** | **-0.56** | **-0.58** | | | | | |
| MTL | -0.08 | **0.16** | **0.31** | **0.14** | 0.03 | -0.02 | -0.07 | 0.14 | 0.14 | 0.27 | -0.24 | **-0.31** | **-0.18** | -0.21 | **-0.31** | **-0.30** | **-0.33** | **-0.44** | **-0.42** | **-0.55** | **-0.57** | | | | |
| GI | **-0.59** | **0.19** | **0.35** | **0.05** | **0.55** | 0.06 | **-0.49** | **0.60** | **0.65** | **0.29** | -0.29 | **-0.37** | **-0.33** | -0.39 | **-0.47** | **-0.55** | **-0.64** | **-0.85** | **-0.63** | **0.12** | **0.24** | **0.47** | | | |
| OIL | **-0.44** | **0.65** | **0.39** | 0.48 | **0.26** | 0.32 | **-0.37** | **0.46** | 0.21 | **0.32** | -0.33 | **-0.42** | **-0.40** | -0.24 | -0.36 | **-0.31** | **-0.30** | **-0.34** | **-0.27** | **-0.25** | **-0.24** | **-0.03** | **0.54** | | |
| TW$ | **-0.50** | **0.48** | **0.43** | **0.39** | **0.48** | 0.20 | **-0.63** | **0.26** | **0.33** | **0.37** | -0.38 | **-0.47** | **-0.48** | 0.32 | **0.54** | **0.49** | **0.46** | **0.73** | **0.56** | **0.45** | **0.36** | **0.37** | **0.45** | **0.35** | |
| VIX | **-0.55** | **0.15** | **0.48** | 0.06 | **-0.66** | 0.05 | **-0.52** | **0.27** | **0.29** | **0.40** | -0.44 | **0.52** | **0.54** | 0.41 | **0.48** | **0.59** | **0.27** | **0.77** | **0.77** | **0.57** | **0.66** | **0.57** | **0.63** | **0.64** | **0.31** |

This table presents the output of Pearson correlation analysis for monthly (1996 M01 to 2020 M02) firm characteristic variables sorted on (2 × 3) and macroeconomic variables, domestic and international. MKT is the pooled market returns of all the countries less one-month US Treasury bill rate. At the end of each year (June), stocks are allocated into two size groups using 90$^{th}$ and 10$^{th}$ percentiles to **represent** big (B) and small (S) stocks, respectively. Stocks are further assigned independently to three book-to-market equity (BM), investment (Inv), operating profitability (OP), Liquidity (LIQ), Momentum (MOM), predictability (PRD) and persistence (PRT) groups, using 30th and 70th percentiles of individual country stocks. HML are the portfolios formed from the intersection of the Size and BM sorts (2 × 3), investment, profitability, leverage, liquidity, momentum, predictability, and persistence factors, CMA, RMW, ROA, IML, UMD, PMU and PMN, use six value weight portfolios from the intersection of the Size and the subsequent characteristic sorts. SMB, size factor (Small Minus Big) is the average return on the twenty-seven small stock portfolios minus the average return on the twenty-seven big stock

portfolios. Domestic macroeconomic variables are DEI (changes in expected inflation), UI (unanticipated inflation), LIQ (aggregate liquidity), REQ (regulatory quality) ROL (rule of law), VOL (returns volatility), and MS (broad money supply, M2). Global macroeconomic variables are AGRIC (agricultural commodity index), UCC (US Consumer confidence), GTP (changes in global term premium), GDS (changes in global default spread), Metal (return on composite metal index), GI (excess return of Morgen Stanley Capital International Index), OIL (return on crude oil prices), TW$ (US dollar broad trade-weighted exchange Index), VIX (US volatility index). Figures indicated in bold represent significance level at *t*-stat>2.0.

### 4.4 Principal Components Analysis on Demeaned Returns

Principal Components Analysis is primarily employed in this study to determine covariance matrix of the demeaned stock returns. Pukthuanthong et al. (2019) posit that true risk factors must be related to the covariance matrix of returns. The true risk factors must be the underlying drivers of returns and should be able to produce a risk-reward ratio worthy of compensating financial asset investors.

Stock prices and hence stock returns should vary with innovations in the underlying drivers of returns. But the degree of this response varies considerably depending on the structure, trading mechanisms and level of technology existing in a particular market. The efficient markets hypothesis of Fama (1970) for instance offers an elegant theoretical explanation of the impact of information and quality of information on stock prices and, subsequently, returns. The theory postulates that stock prices should consistently reflect all material information about the stock as soon as the information is available. By extension, changes in stock prices reflect information about the main underlying economic drivers capable of influencing a firm's future cash flows and profits. It should follow, therefore, that determining the underlying drivers equals determining the true risk factors[23] influencing those stock returns. PCA as applied in this study aids this process by combining the drivers of risk into a few orthogonal principal components[24]. Consequently, if the first two, three or four principal components are found to be significant in the test, then we deduce the existence of more than one risk drivers in the returns of that particular stock market.

[23] Information processed by the market mechanisms.
[24] For ease of consistency, 10 principal components are predetermined for all the 12 countries in the developing equity category.

**Table 7: Principal Components Analysis of Demeaned Stock Returns**

| | Argentina | | Bahrain | | Bangladesh | | Croatia | | Jordan | |
|---|---|---|---|---|---|---|---|---|---|---|
| Component | Proportion | Cumulative | Proportion | Cumulative | Proportion | Cumulative | Proportion | Cumulative | Proportion | Cumulative |
| Comp1 | 0.36 | 0.36 | 0.41 | 0.41 | 0.24 | 0.24 | 0.55 | 0.55 | 0.21 | 0.21 |
| Comp2 | 0.19 | 0.55 | 0.08 | 0.49 | 0.19 | 0.43 | 0.11 | 0.66 | 0.16 | 0.37 |
| Comp3 | 0.13 | 0.68 | 0.05 | 0.54 | 0.13 | 0.56 | 0.06 | 0.72 | 0.14 | 0.51 |
| Comp4 | 0.11 | 0.79 | 0.04 | 0.58 | 0.06 | 0.62 | 0.06 | 0.78 | 0.11 | 0.62 |
| Comp5 | 0.09 | 0.88 | 0.04 | 0.62 | 0.05 | 0.67 | 0.05 | 0.83 | 0.09 | 0.71 |
| Comp6 | 0.03 | 0.91 | 0.03 | 0.65 | 0.05 | 0.72 | 0.04 | 0.87 | 0.07 | 0.78 |
| Comp7 | 0.02 | 0.93 | 0.03 | 0.68 | 0.05 | 0.77 | 0.04 | 0.91 | 0.05 | 0.83 |
| Comp8 | 0.02 | 0.95 | 0.03 | 0.71 | 0.04 | 0.81 | 0.03 | 0.94 | 0.03 | 0.86 |
| Comp9 | 0.01 | 0.96 | 0.02 | 0.73 | 0.03 | 0.84 | 0.03 | 0.97 | 0.01 | 0.87 |
| Comp10 | 0.01 | 0.97 | 0.02 | 0.75 | 0.01 | 0.85 | 0.02 | 0.99 | 0.01 | 0.88 |
| | Kazakhstan | | Kenya | | Kuwait | | Lithuania | | Mauritius | |
| Comp1 | 0.21 | 0.21 | 0.25 | 0.25 | 0.21 | 0.21 | 0.34 | 0.34 | 0.29 | 0.29 |
| Comp2 | 0.14 | 0.35 | 0.11 | 0.36 | 0.14 | 0.35 | 0.15 | 0.49 | 0.19 | 0.48 |
| Comp3 | 0.13 | 0.48 | 0.10 | 0.46 | 0.11 | 0.46 | 0.13 | 0.62 | 0.14 | 0.62 |
| Comp4 | 0.11 | 0.59 | 0.07 | 0.53 | 0.09 | 0.55 | 0.09 | 0.71 | 0.12 | 0.74 |
| Comp5 | 0.04 | 0.63 | 0.05 | 0.58 | 0.07 | 0.64 | 0.06 | 0.78 | 0.04 | 0.78 |
| Comp6 | 0.01 | 0.64 | 0.03 | 0.61 | 0.06 | 0.72 | 0.04 | 0.82 | 0.04 | 0.81 |
| Comp7 | 0.01 | 0.65 | 0.02 | 0.63 | 0.03 | 0.75 | 0.03 | 0.85 | 0.03 | 0.85 |
| Comp8 | 0.01 | 0.66 | 0.02 | 0.65 | 0.02 | 0.77 | 0.03 | 0.88 | 0.03 | 0.88 |
| Comp9 | 0.00 | 0.66 | 0.02 | 0.67 | 0.01 | 0.78 | 0.03 | 0.92 | 0.03 | 0.91 |
| Comp10 | 0.00 | 0.66 | 0.02 | 0.69 | 0.01 | 0.79 | 0.03 | 0.95 | 0.29 | 0.95 |
| | Morocco | | Nigeria | | Oman | | Pakistan | | Romania | |
| Comp1 | 0.17 | 0.17 | 0.16 | 0.16 | 0.21 | 0.21 | 0.22 | 0.22 | 0.28 | 0.29 |
| Comp2 | 0.12 | 0.29 | 0.14 | 0.3 | 0.17 | 0.38 | 0.19 | 0.4 | 0.23 | 0.51 |
| Comp3 | 0.09 | 0.38 | 0.11 | 0.41 | 0.11 | 0.49 | 0.15 | 0.56 | 0.14 | 0.66 |
| Comp4 | 0.07 | 0.45 | 0.1 | 0.51 | 0.07 | 0.55 | 0.13 | 0.69 | 0.09 | 0.75 |

| | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| Comp5 | 0.06 | 0.51 | 0.06 | 0.57 | 0.02 | 0.57 | 0.08 | 0.77 | 0.03 | 0.77 |
| Comp6 | 0.03 | 0.54 | 0.05 | 0.62 | 0.02 | 0.59 | 0.07 | 0.83 | 0.03 | 0.80 |
| Comp7 | 0.03 | 0.57 | 0.02 | 0.64 | 0.02 | 0.61 | 0.03 | 0.86 | 0.03 | 0.83 |
| Comp8 | 0.03 | 0.60 | 0.01 | 0.65 | 0.02 | 0.63 | 0.02 | 0.88 | 0.03 | 0.85 |
| Comp9 | 0.03 | 0.62 | 0.00 | 0.65 | 0.02 | 0.65 | 0.01 | 0.88 | 0.03 | 0.88 |
| Comp10 | 0.03 | 0.65 | 0.00 | 0.65 | 0.02 | 0.67 | 0.01 | 0.89 | 0.02 | 0.90 |
| | | Serbia | | Slovenia | | Sri Lanka | | Tunisia | | Vietnam |
| Comp1 | 0.29 | 0.29 | 0.23 | 0.23 | 0.22 | 0.22 | 0.29 | 0.29 | 0.35 | 0.35 |
| Comp2 | 0.20 | 0.49 | 0.06 | 0.29 | 0.15 | 0.37 | 0.16 | 0.45 | 0.21 | 0.56 |
| Comp3 | 0.08 | 0.57 | 0.06 | 0.35 | 0.09 | 0.46 | 0.12 | 0.57 | 0.13 | 0.62 |
| Comp4 | 0.06 | 0.63 | 0.05 | 0.41 | 0.06 | 0.52 | 0.11 | 0.68 | 0.09 | 0.71 |
| Comp5 | 0.03 | 0.66 | 0.05 | 0.46 | 0.05 | 0.57 | 0.08 | 0.76 | 0.06 | 0.77 |
| Comp6 | 0.01 | 0.67 | 0.05 | 0.51 | 0.03 | 0.60 | 0.04 | 0.80 | 0.04 | 0.81 |
| Comp7 | 0.00 | 0.68 | 0.05 | 0.56 | 0.03 | 0.63 | 0.03 | 0.83 | 0.04 | 0.85 |
| Comp8 | 0.00 | 0.68 | 0.05 | 0.61 | 0.03 | 0.65 | 0.02 | 0.85 | 0.04 | 0.88 |
| Comp9 | 0.00 | 0.68 | 0.05 | 0.66 | 0.03 | 0.68 | 0.01 | 0.86 | 0.03 | 0.92 |
| Comp10 | 0.00 | 0.68 | 0.01 | 0.67 | 0.02 | 0.70 | 0.00 | 0.86 | 0.03 | 0.95 |

Table8 presents the results of Principal Components Analysis (PCA) of the demeaned stock returns from developing equity markets. The table reports the proportions of the variance of returns accounted for by each component and the subsequent cumulative variance explained.

Table **8** reports the empirical output of PCA analysis for each country in the developing equity market category. In each country, 10 Principal Components (henceforth 10 PCs) which generally account for over 65% of the volatilities in stock reruns across the board are extracted. This yardstick is not backed by any specific scientific, mathematical, or statistical justification, but is in place to allow for comparative analysis of all the countries included in the sample. Even though ad hoc, using only 10 PCs from each country does not convolute the factor identification process and plausibly permits a comprehensive comparative analysis of the PCs from each country included in the study.

An examination of the extracted PCs across the panels appears to reveal a common trend where the first PCs tend to account for at least 36% of the total variance and about 4 PCs generally describe over 60% of total variance in returns. This observation appears, in the preliminary sense, to support our hypothesis of the existence of multiple factors influencing the cross-section of returns in developing equity markets. For instance, the first PC accounts for 35% of the total variance for Argentina with 4 PCs controlling close to 80% of total variation in the covariance matrix of return. In Bahrain, the first PC controls up to 41% of stock volatility, and about 5 PCs account for over 83% of all variation. Bangladesh also portrays a similar picture where the first PC is dominant followed by the second PC, and 5 PCs control over 60% of total return volatilities.

Looking across the panel, Croatia stands out as a market almost dominated by few pervasive risk drivers. The first Principal Component account for a massive 55% of total return variations and 4 principal components account for close to 90% of total return volatility. This picture is consistent for most of these countries with the exception of Nigeria, Morocco, and Oman. The three countries' economies significantly rely on crude oil production, and it is interesting to pin down why their return volatilities seems to be potentially spread across many return determinants. Nonetheless, the similarity displayed across the markets with similar

characteristics is not unusual as studies such as Bilson et al. (2001) have established that markets with related features have similar sensitivities to common factors. Furthermore, as a consequence of increased financial markets integration across the world as enumerated by Dong and Yoon (2019), factors influencing return generating processes across countries are potentially similar. The next phase of this study is dedicated to identifying the (set of) factors or variables closely related to the covariance matrix of returns described in this subsection.

### 4.5 Factor Identification

The information contained in the orthogonal principal components extracted suggests the existence of multiple factors influencing stock returns. Therefore, attaining the identities of the factors that seem to be closely and significantly correlated to these covariance matrices of returns is a significant step and vital contribution of this study to asset pricing particularly in developing equity markets. This section attempts to identify such factors.

#### 4.5.1 Canonical Correlation Analysis

The job of identifying the underlying drivers of volatility in returns in this study is carried out using Canonical Correlation Analysis (CCA). CCA procedure is capable of determining the best linear combination between two sets of variables, usually, a group of dependent and independent variables, thus maximizing the resulting correlation coefficients ordered from the strongest to the weakest (Malacarne, 2014). The procedure is conducted in two steps. The first step performs dimensionality reduction of the multivariate datasets in the study. For this study, the 10 PCs extracted from the PC analysis in each of the countries and the 26 proposed candidate risk factors taken through CCA to determine the identity of the suspected underlying drivers of volatility and hence risk in the sampled markets. In the second step, each of the 10 canonical variates (also known as the eigenvector weights of the 10 PCs) are regressed on the actual values of the 26 candidate risk factors and statistically significant variables are

designated as the real candidate risk factors responsible for return variations and possibly command risk premium in each market sampled.

The step one procedure produces canonical pairs or canonical variates. The pairs can also be referred to as the square roots of eigenvalues from the dimensionally reduced variables in the analysis (Rencher and Christensen, 2012, p. 387). Maximum eigenvalues, or the largest squared canonical correlation, produce the best measures of the correlation between the two sets of variables and are usually reported as the first canonical correlation coefficient. Given that there are many candidate risk factors in this study, several canonical variates are produced, and the process ensures that each is orthogonal to the subsequent variates with a particular linear relationship. Canonical correlation orders these canonical variates from largest to smallest based on squared multiple correlations (Pukthuanthong et al., 2019). Consequently, the first coefficient produces the maximum correlation between the eigenvector weights of the multivariate variables included in the analysis.

Put differently, the first canonical coefficient is a linear combination, or canonical variates, of the first two sets of variables, i.e., the incoming 10 PCs and the 26 candidate risk factors. Let, for example, $\boldsymbol{a}_1$ denote the first canonical variate of the 10 PCs and $\boldsymbol{b}_1$ the first canonical variate of the 26 candidate risk factors. $\boldsymbol{a}_1$ and $\boldsymbol{b}_1$ can also be referred to as the first product of dimensionality reductions of the two sets of variables in the analysis producing the first and the highest linear combination of variables in both sets. The process ensures that $\boldsymbol{a}_1$ yields maximum correlation with $\boldsymbol{b}_1$ and are orthogonal to the subsequent canonical roots. The second canonical variates say, $\boldsymbol{a}_2$ and $\boldsymbol{b}_2$ respectively, calculated the same way as the first set, produces the second-highest linear combination of the two sets of variables. The number of non-zero (canonical pairs) solutions is limited to the smallest dimensionality of the two data sets (Rencher and Christensen, 2012). In the sample here, there can only be a maximum of 10 canonical variates and canonical correlation coefficients produced. For each of the 20

countries, 10 canonical variates are calculated, and a maximum of 10 canonical correlation coefficients are sorted from the largest to the smallest reported.

Results of canonical correlations analyses are reported in Table **9**. The first canonical correlation for each country is the highest followed by the second and down to the smallest ($10^{th}$) canonical variate. $z$-statistics, reported in Table **9**, indicate statistical powers of correlation between canonical variates and the variables included in the analysis. Determination of factors or variables highly related to the covariance matrix of returns is based on the values of $z$-statistics. For this study, we adopt a standard cut point, where if the value of $z - stat$ >2, then the variable is selected as a significant driver of returns variations in the markets tested.

Table **9** shows that Argentina produces up to 4 statistically significant canonical variates and canonical correlations. The first canonical variate, as expected has the highest canonical correlation coefficient of 0.86 and is statistically significant at 1% level as indicated by $z$-stat value of 11.3. This is closely followed by the second canonical variate with a canonical coefficient of 0.73 and statistically significant at 1% with a z-stat value of 7.16. The third and fourth canonical coefficients are correspondingly statistically significant at less than 5% level. Interestingly, Bahrain only produces two strongly statistically significant canonical correlations. This may mean that there are just a few dominant pervasive risk factors that control the risk structure in Bahrain's equity market or that factors controlling return variations in Bahrain are closely related.

**Table 8: Canonical Correlation between Factor Candidates and Demeaned Returns**

| Canonical Variate | Argentina | | Bahrain | | Bangladesh | | Croatia | | Jordan | |
|---|---|---|---|---|---|---|---|---|---|---|
| | Canonical Correlation | $z-$stat | Canonical Correlation | $z-$stat | Canonical Correlation | $z-$stat | Canonical Correlation | $z-$stat | Canonical Correlation | $z-$stat |
| 1 | 0.86 | **11.30** | 0.88 | **13.56** | 0.69 | **8.64** | 0.84 | **9.72** | 0.77 | **8.48** |
| 2 | 0.73 | **7.16** | 0.81 | **9.77** | 0.60 | **7.00** | 0.70 | **9.14** | 0.69 | **5.22** |
| 3 | 0.59 | **4.69** | 0.26 | 1.84 | 0.47 | **3.09** | 0.23 | **2.05** | 0.50 | **2.68** |
| 4 | 0.39 | **2.89** | 0.18 | 1.01 | 0.45 | **2.07** | 0.18 | 1.09 | 0.36 | **2.16** |
| 5 | 0.32 | 1.73 | 0.12 | 0.85 | 0.25 | 1.17 | 0.16 | 0.91 | 0.26 | 1.09 |
| 6 | 0.19 | 0.82 | 0.11 | 0.18 | 0.23 | 1.25 | 0.16 | 0.89 | 0.24 | 0.35 |
| 7 | 0.15 | 0.74 | 0.02 | 0.09 | 0.16 | 1.00 | 0.07 | 0.83 | 0.16 | 0.35 |
| 8 | 0.09 | 0.41 | 0.01 | 0.08 | 0.13 | 0.92 | 0.05 | 0.72 | 0.13 | 0.31 |
| 9 | 0.08 | 0.25 | 0.01 | 0.02 | 0.12 | 0.05 | 0.03 | 0.28 | 0.11 | 0.23 |
| 10 | 0.03 | 0.09 | 0.00 | 0.01 | 0.09 | 0.01 | 0.01 | 0.09 | 0.08 | 0.11 |
| | Kazakhstan | | Kenya | | Kuwait | | Lithuania | | Mauritius | |
| 1 | 0.77 | **7.59** | 0.81 | **9.35** | 0.75 | **9.38** | 0.57 | **8.65** | 0.68 | **7.55** |
| 2 | 0.64 | **7.32** | 0.76 | **7.20** | 0.57 | **3.89** | 0.51 | **7.00** | 0.61 | **6.20** |
| 3 | 0.58 | **2.26** | 0.67 | **5.64** | 0.50 | **2.93** | 0.50 | **4.67** | 0.50 | **2.31** |
| 4 | 0.45 | **2.11** | 0.51 | **2.57** | 0.34 | 1.20 | 0.46 | **2.89** | 0.29 | 1.39 |
| 5 | 0.27 | 1.09 | 0.21 | 1.35 | 0.27 | 1.14 | 0.43 | 1.81 | 0.19 | 1.18 |
| 6 | 0.26 | 0.21 | 0.12 | 1.25 | 0.26 | 0.98 | 0.41 | 1.25 | 0.18 | 1.60 |
| 7 | 0.22 | 0.12 | 0.11 | 0.92 | 0.17 | 0.90 | 0.38 | 1.25 | 0.14 | 0.11 |
| 8 | 0.15 | 0.01 | 0.11 | 0.90 | 0.14 | 0.07 | 0.31 | 0.36 | 0.07 | 0.09 |
| 9 | 0.13 | 0.01 | 0.07 | 0.07 | 0.13 | 0.04 | 0.20 | 0.18 | 0.05 | 0.01 |
| 10 | 0.02 | 0.00 | 0.04 | 0.01 | 0.09 | 0.02 | 0.17 | 0.03 | 0.02 | 0.01 |
| | Morocco | | Nigeria | | Oman | | Pakistan | | Romania | |
| 1 | 0.86 | **7.59** | 0.81 | **6.44** | 0.75 | **6.38** | 0.57 | **11.65** | 0.78 | **7.55** |
| 2 | 0.70 | **7.32** | 0.73 | **5.26** | 0.57 | **2.82** | 0.51 | **7.49** | 0.65 | **4.11** |
| 3 | 0.60 | **2.26** | 0.69 | **3.70** | 0.50 | **2.22** | 0.50 | **4.67** | 0.56 | **2.27** |
| 4 | 0.54 | **2.11** | 0.57 | **2.57** | 0.34 | 1.20 | 0.46 | **2.89** | 0.34 | 1.39 |
| 5 | 0.27 | 1.09 | 0.21 | 1.35 | 0.27 | 1.14 | 0.45 | **2.01** | 0.27 | 1.18 |

| | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| 6 | 0.26 | 0.21 | 0.12 | 1.25 | 0.26 | 0.98 | 0.44 | 1.25 | 0.18 | 1.60 |
| 7 | 0.22 | 0.12 | 0.11 | 0.92 | 0.17 | 0.90 | 0.43 | 1.25 | 0.14 | 0.11 |
| 8 | 0.15 | 0.01 | 0.10 | 0.90 | 0.14 | 0.07 | 0.41 | 0.36 | 0.07 | 0.09 |
| 9 | 0.13 | 0.00 | 0.07 | 0.07 | 0.13 | 0.04 | 0.39 | 0.18 | 0.05 | 0.01 |
| 10 | 0.02 | 0.00 | 0.04 | 0.01 | 0.09 | 0.01 | 0.37 | 0.03 | 0.02 | 0.01 |
| | Serbia | | Slovenia | | Sri Lanka | | Tunisia | | Vietnam | |
| 1 | 0.81 | **7.19** | 0.79 | **11.13** | 0.75 | **10.23** | 0.88 | **6.24** | 0.89 | **9.13** |
| 2 | 0.69 | **5.57** | 0.69 | **8.27** | 0.71 | **7.88** | 0.73 | **5.31** | 0.72 | **6.57** |
| 3 | 0.52 | **3.91** | 0.64 | **4.97** | 0.52 | **5.52** | 0.62 | **4.01** | 0.57 | **4.97** |
| 4 | 0.45 | **2.31** | 0.55 | **2.37** | 0.45 | **3.29** | 0.49 | **2.29** | 0.45 | **2.37** |
| 5 | 0.37 | 1.43 | 0.39 | 1.43 | 0.33 | 1.43 | 0.34 | 1.43 | 0.38 | 1.81 |
| 6 | 0.27 | 1.29 | 0.26 | 1.29 | 0.17 | 1.29 | 0.27 | 1.29 | 0.31 | 1.59 |
| 7 | 0.18 | 1.04 | 0.19 | 1.04 | 0.11 | 1.04 | 0.19 | 1.04 | 0.27 | 1.24 |
| 8 | 0.15 | 0.12 | 0.14 | 0.52 | 0.10 | 0.52 | 0.16 | 0.62 | 0.15 | 0.82 |
| 9 | 0.13 | 0.07 | 0.11 | 0.47 | 0.08 | 0.47 | 0.11 | 0.27 | 0.11 | 0.49 |
| 10 | 0.11 | 0.02 | 0.10 | 0.42 | 0.03 | 0.42 | 0.09 | 0.12 | 0.06 | 0.22 |

Notes: Table 9 reports canonical correlations between the extracted principal components of demeaned monthly stock returns (1996 M01 to 2020 M02) and the canonical variates generated between the 10 principal components of the demeaned stock returns and the 26 candidate risk factors comprising of factors constructed on firm characteristics, factors derived from domestic macroeconomic variables and factors derived from global macroeconomic variables. The canonical correlations are deemed consistent with the economic expectations and significantly different from zero at the 5% significance level. The $z-$stats expressed in bold are positive and significantly different from zero at 5% level.

Croatia reports three statistically significant canonical variates, in which the first canonical variate produces the highest correlation coefficient at 0.84 followed closely by the second canonical variate coefficient at 0.70, while the third significant coefficient seemingly indicates weak significance with a coefficient of 0.23, indicating a significant leap from the first and the second canonical variates. In all, the first three canonical variates are significant as indicated by the $z-$stat values which are all above the critical value of 2. The result of the canonical correlation analysis of Croatia seemingly mirrors the earlier PCA output where the first component accounted for most of the total volatility followed by the second and began to drastically dwindle from the third component.

An interesting pattern emerges from Table **7,** in which 14 out of 20 countries produce at least 4 significant canonical variates. A departure is nonetheless noticed in countries like Bahrain and Croatia where the first two canonical variates seem to account for most of the significant variations in the returns. It remains to be seen if these significant canonical variates are significantly related to the actual values of the 26 candidate risk factors. This can only be determined by running a multiple regression using the canonical variates as the dependent variables on the actual values of the 26 candidate risk factors as the independent variables, then using the resultant $z$-statistics to determine the significance of the independent variables. The results of this procedure are reported in Table **10.**

To determine the significant relations between the candidate risk factors and the covariance matrix of returns (10 PCs), the following procedure is implemented; first, we take the eigenvector weights of the 10 PCs in each country and construct a weighted average of the 10 PCs canonical variates. The next procedure involves running multiple regressions using each of the 10 canonical variates as dependent variables on actual values of the 29 candidate risk factors over the Sample period. Each candidate factor's absolute $t$-statistic indicates its significance and significant factors must have an absolute $t$-stat of at least 2.0.

**Table 9: Significance Test of Factor Candidates**

| Country | Argentina | Bahrain | Bangladesh | Croatia | Jordan | Kazakhstan | Kenya | Kuwait | Lithuania | Mauritius |
|---|---|---|---|---|---|---|---|---|---|---|
| MKT | **2.87** | **2.83** | 1.52 | 1.32 | 1.13 | 1.30 | **3.26** | **3.65** | 0.19 | **2.62** |
| SMB | **2.67** | **2.34** | 1.23 | 1.62 | **3.28** | 1.06 | 1.51 | **3.56** | 0.74 | **2.35** |
| HML | **2.56** | 0.24 | **2.16** | 1.91 | 1.37 | **2.92** | **3.15** | **2.95** | 1.92 | **3.10** |
| CMA | 1.72 | **2.40** | 1.49 | **2.20** | 1.65 | 1.62 | 1.20 | **2.20** | 1.23 | 1.78 |
| RMW | **2.31** | **2.38** | **2.02** | **2.62** | **2.81** | 1.20 | **2.79** | **2.87** | **1.96** | 1.27 |
| DE | 1.79 | 1.25 | 1.65 | **1.97** | **2.07** | 1.10 | 1.14 | 1.18 | **2.20** | **2.17** |
| IML | 1.13 | **2.01** | **2.59** | 1.76 | 1.24 | 0.33 | 1.62 | **2.04** | 1.67 | **2.40** |
| UMD | **2.19** | **5.19** | **2.84** | **2.27** | **2.37** | **3.02** | **3.21** | 1.40 | **2.20** | **2.27** |
| PMU | 1.18 | **4.03** | 1.07 | **5.45** | **2.21** | **4.04** | 1.46 | 1.29 | 1.13 | **3.17** |
| PMN | 1.41 | 1.40 | **3.84** | 1.75 | **5.01** | **3.30** | **3.14** | **3.15** | **2.15** | 1.09 |
| DEI | **3.31** | 1.25 | 1.72 | **2.57** | **2.56** | **4.37** | 1.89 | 1.82 | 2.84 | 1.68 |
| UI | **2.22** | **2.22** | 1.04 | **2.17** | **2.31** | **3.49** | **3.08** | **2.36** | 1.13 | **2.21** |
| LIQ | **3.28** | **3.22** | **3.15** | **2.88** | **3.73** | 1.27 | **3.22** | **2.99** | 1.64 | **4.20** |
| REQ | **1.97** | **2.43** | **4.42** | 0.92 | **2.40** | 1.16 | **2.29** | **3.12** | 1.64 | **3.86** |
| ROL | **3.12** | **1.99** | **3.09** | 1.33 | **2.30** | 1.06 | **2.10** | **2.99** | 0.28 | 1.24 |
| VOL | **2.93** | **3.04** | **3.01** | **2.87** | **5.90** | **3.15** | **4.38** | **2.61** | **2.33** | **2.60** |
| MS | 0.53 | 1.88 | 1.68 | **2.11** | 0.88 | 2.08 | **3.04** | 1.52 | 1.46 | **2.75** |
| AGR | **2.92** | 1.83 | **2.84** | 0.55 | 1.05 | 0.74 | **3.14** | 1.51 | 0.13 | **2.89** |
| CC | 1.62 | **2.99** | 1.51 | 1.34 | **4.39** | **6.79** | **1.96** | **3.72** | **2.75** | 1.82 |
| GTP | **2.97** | **2.24** | 1.64 | 1.47 | **2.89** | 1.73 | 1.41 | **3.83** | **2.43** | **3.20** |
| GDS | **3.15** | **2.29** | 1.65 | 1.45 | **2.87** | 1.37 | 1.61 | **4.22** | **2.82** | **3.41** |
| MTL | 1.82 | **2.60** | 0.31 | 0.95 | 1.18 | 1.17 | 1.14 | **3.74** | 1.51 | 1.14 |
| GI | 1.71 | **2.66** | 1.35 | 0.85 | **2.32** | 1.41 | **2.43** | **3.94** | 1.53 | **2.48** |
| OIL | 1.60 | **2.73** | **2.41** | 0.75 | **3.47** | **4.97** | **2.61** | **4.14** | 1.54 | **2.70** |
| TW$ | 1.50 | **2.80** | **2.35** | 0.67 | **3.52** | **5.22** | **3.91** | **4.34** | 1.57 | **5.14** |
| VIX | 1.39 | **2.86** | **2.29** | 0.57 | **3.56** | **2.13** | 1.86 | **4.54** | 1.59 | **5.36** |

| | Morocco | Nigeria | Oman | Pakistan | Romania | Serbia | Slovenia | Sri Lanka | Tunisia | Vietnam |
|---|---|---|---|---|---|---|---|---|---|---|
| MKT | **2.75** | **1.97** | **3.34** | **2.20** | **2.96** | **2.20** | **4.06** | **4.10** | **2.11** | **2.59** |
| SMB | **2.27** | 1.45 | 1.10 | 1.55 | **3.15** | 0.98 | 1.37 | **3.41** | 0.71 | 1.27 |
| HML | **2.46** | 0.23 | **2.55** | 2.81 | 1.31 | 1.84 | **3.03** | **2.83** | **1.84** | **2.97** |
| CMA | 1.65 | 1.72 | 1.39 | 1.13 | 1.54 | 1.55 | 1.11 | **2.11** | 1.14 | 0.93 |
| RMW | 1.27 | **2.36** | **0.05** | 1.57 | 1.76 | 1.15 | **2.49** | **2.76** | **1.92** | 1.23 |
| DE | 1.72 | 1.21 | 1.58 | **1.97** | **2.07** | 1.99 | 1.06 | 2.07 | **1.13** | **1.16** |
| IML | **2.85** | **1.87** | **1.51** | 1.94 | 1.19 | 1.88 | 1.55 | **1.96** | **2.58** | 1.32 |
| UMD | **2.10** | **3.83** | **2.72** | **2.19** | **2.27** | **2.90** | **3.09** | 2.33 | **2.11** | **2.19** |
| PMU | 1.13 | **3.87** | **2.28** | 1.30 | **2.13** | **3.88** | 1.40 | 1.24 | 1.09 | **3.04** |
| PMN | **2.29** | 1.35 | **3.68** | 1.69 | **4.80** | **3.18** | **3.02** | 1.07 | **2.05** | 1.00 |
| DEI | **3.19** | 1.21 | **2.59** | **2.47** | **2.46** | **4.19** | 1.81 | 1.74 | **2.72** | 1.62 |
| UI | **2.14** | **2.14** | **2.88** | **2.08** | **2.22** | **3.35** | **2.95** | **2.26** | 1.09 | **2.12** |
| LIQ | **3.15** | **4.24** | **3.06** | **3.95** | **3.59** | **2.32** | **3.18** | **2.96** | **2.72** | **3.84** |
| REQ | 1.89 | **2.33** | **2.05** | 0.89 | **2.31** | 1.11 | **3.26** | **3.00** | 1.57 | **3.71** |
| ROL | **3.00** | 1.91 | **1.87** | 1.28 | **2.21** | 1.01 | **3.14** | **2.87** | 0.26 | 1.20 |
| VOL | **2.85** | **2.96** | **2.89** | **1.71** | **5.67** | **0.91** | **4.20** | 0.39 | 0.13 | **2.50** |
| MS | 0.51 | 1.82 | 1.62 | **2.02** | 0.84 | 2.00 | **2.90** | 1.45 | 1.41 | **2.64** |
| AGR | 1.71 | 1.75 | 1.62 | 0.53 | 3.11 | 0.72 | **3.97** | **2.51** | 0.13 | **2.78** |
| CC | 1.55 | **1.77** | 1.44 | 1.29 | **4.21** | **6.51** | **5.05** | **3.58** | **2.64** | 1.74 |
| GTP | **2.97** | **1.13** | 1.64 | 1.47 | **2.89** | **5.06** | **4.74** | **3.83** | **2.43** | **2.09** |
| GDS | **3.15** | **1.18** | 1.65 | 1.45 | **2.87** | **5.81** | **4.94** | **4.22** | **2.82** | **3.41** |
| MTL | 1.74 | **1.39** | 1.32 | 0.91 | **2.15** | **2.10** | **2.06** | **3.60** | 1.45 | **2.08** |
| GI | 1.64 | **1.45** | 1.25 | 0.82 | **3.30** | **4.55** | **4.46** | **3.79** | 1.47 | **2.29** |
| OIL | **2.64** | **2.62** | **2.31** | **2.95** | **2.23** | **2.55** | **2.42** | **3.97** | 1.49 | **1.39** |
| TW$ | **2.54** | **2.69** | **2.25** | **2.85** | **3.37** | **5.01** | **4.81** | **4.16** | **2.61** | **4.94** |
| VIX | 1.33 | **1.64** | **2.20** | 0.54 | **1.20** | 1.91 | 1.65 | **3.24** | 1.52 | **2.93** |

This table reports significant tests of the canonical variates and real values of the candidate risk factors for monthly (1996 M01 to 2020 M02) firm characteristic variables sorted on $(2 \times 3)$ and macroeconomic variables, domestic and international. Significance tests marked in bold indicate 5% level of significance. MKT is the individual country market returns of all the firms with complete data less one-month US Treasury bill rate. At the end of each year

(June), stocks are allocated into two size groups using $70^{th}$ and $30^{th}$ percentiles to represent big (B) and small (S) stocks, respectively. Stocks are further assigned independently to three book-to-market equity (BM), investment (Inv), operating profitability (OP), Liquidity (LIQ), Momentum (UMD), predictability (PRD), and persistence (PRT) groups, using 30th and 70th percentiles of individual country stocks. HML is the portfolios formed from the intersection of the Size and BM sorts ($2 \times 2$), investment, profitability, leverage, liquidity, momentum, predictability, and persistence factors, CMA, RMW, ROA, IML, UMD, PMU, and PMN, use six value weight portfolios from the intersection of the Size and the subsequent characteristic sorts. SMB, size factor (Small Minus Big) is the average return on the eighteen small stock portfolios minus the average return on the eighteen big stock portfolios. Domestic macroeconomic variables are DEI (changes in expected inflation), UI (unanticipated inflation), LIQ (aggregate liquidity), REQ (regulatory quality) ROL (rule of law), VOL (returns volatility), and MS (broad money supply, M2). Global macroeconomic variables are AGRIC (agricultural commodity index), CC (US Consumer confidence), Metal (return on the composite metal index), GI (excess return of Morgen Stanley Capital International Index), OIL (return on crude oil prices), TW$ (US dollar broad trade-weighted exchange Index), VIX (US volatility index).

As expected, there are notable similarities across the countries in the developing equity markets. Results in Table 10 indicate that market factor[25] possibly accounts for risk-return relation in 15 of the 20 countries in the developing equity markets sample. Market factor only fails to significantly influence return variations in Bangladesh, Croatia, Jordan, Kazakhstan, and Lithuania. According to Table 10, all the 15 countries produce a requisite cut-off point of absolute $t$-stat of at least 2 for the market factor. As expected, the factor attracts stronger statistical significance in some countries than others. For instance, Slovenia, Sri Lanka, Oman, Kenya, and Kuwait report the highest t-stats for the market factor in the sample.

Nonetheless, the importance of the market factor in the 15 countries may further intensify the debate surrounding the tenability of CAPM model where market factor is the only risk factor postulated to capture all the return variations in a particular stock market. But evidence also abounds that for the market factor to successfully account for the risk-return relations, efficiency of the portfolio mimicking the market portfolio must be upheld. Efficiency of the underlying portfolio has been advanced as the foundational success of the model, despite the mixed empirical results (Fama and French, 2004). Yet, results provided here potentially indicate the significance of market factor in explaining the majority of the variations in developing equity market returns whose information efficiency remains contentious. This finding further suggests that market beta remains the cornerstone in determining the risk-return relations. Several studies have established that developing equity markets are inefficient or oscillating between weak-form and semi-strong form efficiency. For instance, (Katusiime et al., 2015), and Mobarek and Mollah (2015) all produce evidence complicating the developing

[25] Possibly is used in this sentence advertently to illustrate that we cannot say with certainty whether the significant factor is actually priced or is commanding risk premium in the 9 markets it is found to have strong relationships with the covariance matrix of returns.

markets efficiency debate. This further suggests that market efficiency will continue to attract debate in developing equity markets.

Other attempts to understand market beta pricing in developing equity markets such as Zaremba and Maydybura (2019) find that many of the quantitative trading strategies in frontier stock markets can be synthesized and jointly explained by the market factor alongside size, value, and momentum factors. On the contrary, Boamah (2017) and Selebogo and Kodongo (2020) report insignificant evidence of the market factor to price securities respectively in African and emerging stock markets. Hence, this preliminary indication of the ability of the factor to significantly influence equity returns in these sets of markets is of special interest to this study.

However, as has been repeatedly highlighted in this study, Fama and French (2004) conclude that no conclusive evidence exists to completely reject the market factor in pricing capital securities across the markets. Empirical evidence from both developed and non-developed markets leaves the research on pricing financial assets using market beta an open question (Bai and Green, 2019; Da, Guo, and Jagannathan, 2012; Lewellen and Nagel, 2006). The covariance matrix of returns in three countries, Bangladesh, Croatia, Jordan and Kazakhstan, and Lithuania, as evidenced so far in Table 9, fails to establish a close relationship with the variations in market returns, (that is, the canonical correlation coefficient of market factor is not significant). This evidence, even though not conclusive at this stage, adds to the evidence on the inconsistency of market beta in describing equity returns.

Size factor, SMB, and value factor, HML, are described by Fama and French (1996) as the leading exposures to unknown systematic risk drivers in returns with the ability to subsume many of the anomalous exposures to the systematic drivers of returns. On the contrary, the size factor appears to perform dismally among the developing stock markets in this study, and only

significantly influence return volatility in 8 out of 20 countries in the study. HML on the other hand significantly affects returns variations in 13 countries. Evidence provided in Table 10 reveals that SMB (size factor) is significantly related to covariance matrix of returns in Argentina, Bahrain, Jordan, Kuwait Mauritius, Morocco, Romania, and Sri Lanka.

There is consistent empirical evidence suggesting prevalence of value premium in equity markets out of the U.S. Barry, Goldreyer, Lockwood, and Rodriguez (2002) found that value effect is more pronounced in emerging markets compared to size effect. They established that value factor is more pervasive in describing equity returns in 35 emerging markets and is not influenced by extreme return values, which critically impacts the ability of the size factor in their sample. The extreme returns phenomenon is classical for markets with trading frictions like the ones included in our sample. The evidence of Barry et al. (2002) is corroborated by the findings of Cakici et al. (2013) who also established significant influence of value factor in describing equity returns in emerging equity returns. Lin (2017) also adduced evidence in support of value factor over size factor in the Chinese stock market.

The investment factor, CMA, performs dismally across the countries included in the sample here and is only found to influence return covariance matrix in five countries included in the sample. This finding is not strange, as the "investment anomaly" patterns have been found to strongly manifest in developed markets compared to less developed markets (Li, Zhang, Cai, and Keasey, 2016). Evidence reported in Table 8 indicates that Bahrain, Croatia, Kuwait, and Sri Lanka are the only markets in the sample where investment factor appears to be highly correlated to the return covariance matrix. Zaremba et al. (2018) include these three countries in a broad sample of over 1500 stocks in Middle East frontier equity markets and find conflicting evidence on the ability of CMA to describe returns of 167 anomalies. The weak performance of investment factor in majority of the countries included in this study is therefore

not unexpected. Guo et al. (2017) test the Five-Factor model and find weak evidence of the investment factor in describing average returns.

Operating profitability, RMW, and liquidity, IML factors seem to explain sizeable return variations in 10 and 6 countries, respectively. In contrast to CMA factor, profitability factor has performed moderately well in describing security returns in empirical tests across the globe. Guo et al. (2017) find robust empirical evidence supporting the ability of profitability factor to influence return variations in Chinese stocks. Liquidity factor (Illiquid minus liquid) confirms empirical debate surrounding liquidity risk in developing and emerging equity markets. For instance, Stereńczak, Zaremba, and Umar (2020) conduct a comprehensive analysis of illiquidity premium in 22 frontier stock markets and find no significant evidence supporting the pricing of liquidity in frontier stock markets. They conclude that illiquidity premium does not exist in frontier equity markets.

On the other hand, Altay and Çalgıcı (2019) established that including liquidity betas on the standard asset pricing models like CAPM improves the overall statistical tests powers of the model in Borsa Istanbul. De Groot et al. (2012) document that momentum and profitability factors capture most variations in frontier stock returns due to 'real-life' imperfections that exist in these markets. A closer observation of Table **9** demonstrates that firm-level liquidity measured using the Amihud (2002) procedure is a significant stock market risk driver in 6 of the 20 countries included in the sample. IML's dismal performance realised here perhaps suggests firm-level liquidity does not form part of the decision calculus employed by many investors in these countries. This outcome could be attributed to infrequent trading as some studies have shown that many stocks in developing equity markets possibly have stale prices, suggesting that pricing liquidity at the firm level may not be a straightforward exercise (De

Groot et al., 2012; Stereńczak et al., 2020). Therefore, given this observation, there is thus a possibility that IML may not be the most appropriate proxy for liquidity in these markets.

[26]Thus, this study includes two additional proxies of trading activity, which have received sizeable empirical attention, particularly in markets with infrequent order flows: aggregate liquidity (LIQ) and market-wide volatility. Performance exhibited by aggregate liquidity (LIQ) and market-wide volatility (VOL) across the markets in Table 10 suffices, at this point of the analysis, to vindicate liquidity as a possible important driver of returns in developing equity markets in this study. The two variables are found to significantly influence returns variations in 17 and 16 countries, respectively. Market liquidity and volatility are intricately interrelated (Chung and Chuwonganant, 2018). Volatility shocks can induce greater liquidity pressures which in turns are possibly priced by investors in the marketplace. Chung and Chuwonganant (2018), for instance, produce evidence linking market volatility to stock returns. Their evidence further suggest that higher market volatility induces greater risk premiums and greater illiquidity premiums on stock returns.

The debt-to-equity ratio (DE), a metric used to determine how firms finance their operations, is significant in not more than 6 developing equity markets included in this study. DE is a capital structure decision, where the management of a corporation contends with what amount of debt vis a viz equity is needed to finance the firm's assets and operations. This evidence resonates with empirical observation depicting most of the developing equity markets as lacking well developed and functioning bond markets, which in turn results in high dependence on expensive traditional sources of financing such as bank loans which cannot be traded in the stock markets (Ojah and Kodongo, 2015). For instance, Yartey (2009) document that due to

[26] Few examples of studies who find economically significant evidence of liquidity premium on cross-section of stock returns include An, Ho, and Zhang (2019), Krishna and Sadowski (2019), Brennan, Chordia, Subrahmanyam, and Tong (2012), and Narayan and Zheng (2011)

lack of a well-functioning debt market, Ghanaian firms tend to use short-term debts and more equity in financing their assets. This, as the author reports, shifts the balance of financing to equity than debt in many firms' financing mix. Mu, Phelps, and Stotsky (2013) list factors such as interest rates volatility, institutional weaknesses, level of economic developments as the major impediments to bonds investment in the frontier markets, especially those of Africa. However, in what appears to be contrasting Stotsky's (2013) findings, domestic macro variables like money supply (a monetary policy decision, usually addressed by interest rates control), the rule of law and regulatory quality do not produce strong influence on returns in the developing equity markets under investigation here.

Results in Table 9 further elucidate some inconsistencies about the impact of inflation on stock returns variations. Theoretically, moderate inflation is desirable for a healthy economy since it stimulates businesses and consumers to commit more money to goods and services in the economy (Cooley and Hansen, 1991). However, a consistently rising inflation poses a threat to the value of investment returns and can be counterproductive as it erodes investors' purchasing power. It is expected that inflation may lead to negative returns, especially on investments comprising of fixed income securities. Developing equity markets are characterized by relatively high and persistent inflation compared to emerging and developed markets (Farooq and Ahmed, 2018).

The relationship between inflation and stock returns has had an inconclusive empirical debate. Early inquiries such as Fama and Schwert (1977), Jaffe and Mandelker (1976), McQueen and Roley (1993), Amihud (1996) found inconsistent results regarding the ability of inflation to price stock returns in various stock markets. In a recent attempt, Antonakakis, Gupta, and Tiwari (2017) incorporate a large group of markets in an international setting and establish that the relationship between inflation and stock returns is evolving. It is nonetheless emerging that

capturing the effects of inflation on the value of investment significantly depends on the aspect of inflation under consideration (Baharumshah, Slesman, and Wohar, 2016).

Studies on asset pricing have explored two measures of inflation, unexpected and expected inflation, and their influence on risk returns relations in various capital markets. The empirical findings comprising the two measures of inflation are equally varying. For instance, Pierdzioch, Risse, Gupta, and Nyakabawo (2019) model the comovement of REIT returns with expected and unexpected inflation, and only find a modest result for unanticipated inflation. Contrary to the established empirical controversy, the two inflation factors adopted in this study, DEI and UI, yield different relationships with the stock return volatility in the developing equity markets in the sampled markets. Inflation surprise or unanticipated inflation (UI) largely produces statistically significant relationship with returns volatilities compared to changes in expected inflation (DEI) across the panel of countries in the sample. These results motivate further empirical interrogation to draw a firm conclusion on which of the inflation variables is specifically important to investors in developing equity markets.

Of the global macroeconomic variables included in the sample, agricultural commodity index, US consumer confidence, global default spread, global term premium, and metal index return fail to significantly move return variation in the majority of the countries; hence these variables may not have to be considered for further interrogation in the next phase of this study. Oil prices, trade-weighted U.S. exchange rates, and the VIX volatility index perform moderately well, as they each influence return volatility in over ten countries in the sample. The strong performance of crude oil prices is not surprising, however, as there is a plethora of empirical evidence documenting the effect of oil prices on stock returns of the calibre of countries included in our study (Akoum, Graham, Kivihaho, Nikkinen, and Omran, 2012; Balcilar, Demirer, and Hammoudeh, 2019).

Results in Table **10** further show that most of the global or international variables manifest significant relationship with the underlying drivers of returns in the developing equity markets. Of significant attention is the trade-weighted US dollar, a variable that measures the appreciation/depreciation of the U.S dollar against a basket of trading partners' currencies. Results provided in Table 9 affirm that the variable influences return variations in 17 of the 20 countries included in the sample. Surprisingly, Agricultural Commodities Index does not seem to significantly move returns in majority of the countries in the sample. However, this is explainable. Countries whose stock variations have strong link to changes in agricultural commodity index depend on agriculture as a significant national budget contributor. Argentina, for example, produces cereals such as corn, wheat, sorghum, and rice for the international markets, hence a significant foreign exchange earner. Kenyan economy, for instance, relies on agricultural productivity since the country produces coffee, tea, avocado, and other horticultural products for the international markets, while Sri Lanka is a significant producer of rice, vegetables, and fruits for the international markets. Mauritius, on the other hand, is a net importer of agricultural produce for domestic consumption and is therefore critically affected by the international prices of agricultural products.

To progress a factor to the next phase of the study, the factor is considered important if it is significantly related to the covariance matrix of returns in at least 10 of the 20 sampled countries. Thus, if Table **10** produces up to 13 significant variables, say in 11 countries, then the 13 variables would easily be adopted for further analysis in the empirical testing stage. To further aid the factor selection process, a group analysis with pooled data is performed, next.

### 4.5.2 Pooled Canonical Correlations Analysis

The analysis conducted so far has been anchored on the simple and restrictive standard principal components analysis (PCA)[27]. This was largely due to data paucity at the country-level which could only permit the use of PCA. Additionally, PCA works perfectly when the number of observations (290 months of observations) exceeds the number of variables (and/or firms with complete data) in the sample. Recall that the procedure demanded that each firm's demeaned returns undergo PCA process to calculate the covariance matrix of returns (then extract 10 PCs), which are later used in the canonical correlation process to determine candidate risk factors significantly related to the underlying risk drivers (covariance matrices of the 10 PCs). The Asymptotic Principal Component Analysis (APCA) procedure is considered superior when dealing with larger dimensions, precisely if the number of variables exceeds the number of observations (Pukthuanthong et al., 2019). This is achieved by forming a pooled sample of all the firms with complete returns data. The pooled sample offers ample diversity to integrate common underlying drivers of volatility in returns across the sampled countries. Sample pooling is consistent with recent asset pricing works in developing equity markets.

Moreover, using pooled sample offers this study a firm ground for discovering the identity of common factors important for returns volatility across the panel of countries in the sample. This is vital to avoid using ad hoc criteria in picking or isolating factors or variables guided only by the number of countries in which they influence total volatility of returns. Inferences made from such a process can be subjective and statistically rudimentary. Hence, conducting analysis using pooled samples of the firms in each of the market categories in the study might make for a more objective criterion. Besides, conducting a pooled study using a mix of

[27] PCA is questioned for its ability to model cross-sectional dependence structure (Richman, 1986). PCA is rigid towards autocorrected series patterns and struggles to model high dimensional data where the number of features exceed the number of observations. Asset pricing research has documented significant information revealed by autocorrelation structure in the return's series, therefore, to suggest a method that does not account for it, is denying the proposed model the right ingredients needed in its formulation.

domestic and global variables subtly addresses the question of integration between the categories of the markets under investigation in this study. In that regard, therefore, we can compare on aggregate, which markets have their returns significantly intertwined with the innovations in the global macroeconomic environment.

Table 11 presents the results of pooled canonical correlations between the asymptotic principal components in panel A, and the significance levels of successful factor candidates in panel B. Panel A thus documents the results of canonical correlations between 10 asymptotic PCs and the 10 canonical variates of the three categories of markets in the study. To counter the possible impact of structural breaks in the series, the samples are divided into two subsample periods. The mechanics of the analysis nonetheless remain the same as has been described in the individual countries' analyses using PCA in the preceding sub-section. Results in panel A indicate that between January 1996 and February 2009, there were only three significant canonical variates in the developing equity markets. In the second subperiod (between 2010 and February 2020) developing equity markets results indicate that up to four canonical variates became significantly related to the covariance matrix of returns. In the full sample, between January 1996 and February 2020, up to five canonical variates were found to be significantly related to overall returns volatility in the developing equity markets.

For emerging markets, the first subperiod produces four significant canonical variates, while the second subperiod produces five significant canonical variates. The entire period of the study found that 6 canonical variates were significant in emerging stock markets. Developed markets results are however consistent across the subsample periods including the base period, where 6 canonical variates were consistently significant. This evidence may suggest time variation in priced factors possibly due to the impact of the global financial crisis on the risk structure of both developing and emerging equity markets.

As can be observed in the table, both the developing and emerging equity markets had 3 and 4 significant canonical variates respectively for the first subperiod, but when the impact and adjustments following GFC subsequently permeate the series, they both respectively register 4 and 5 significant canonical variates. For the entire study period, however, differences begin to emerge as emerging and developed markets both register 6 significant canonical variates, while developing markets produce 5 significant canonical variates. At this point, this empirical output is not clear on the identity of the underlying drivers of volatility. What is clear is that all the markets register presence of multivariate factors.

Despite the impact and effects of the structural breaks, the results in Table 11 further fortifies the hypothesis of multivariate risk factors in developing, emerging, and developed equity markets included in this study. Panel B of Table 11 presents the significance tests of the factor candidates. To derive the significance levels of each factor candidate, we implement a procedure employed by Pukthuanthong et al. (2019). For each canonical pair, the eigenvector weights for the 10 PCs are drawn and the weighted average PCs (the canonical variate for the 10 PCs that produced the canonical correlation for this pair) constructed. Then a multiple regression using each PC's canonical variate as the dependent variable and the 26-factor candidates as the independent variables is run over the 290 months of observation. To mitigate the challenges posed by structural breaks, we break the sample into three. The first regression utilizes data from January 1996 to December 2009 and records the associated $t$-stats. The second subsample is between January 2010 to February 2020, while the last subsample, the baseline test is for the whole sample period, from January 1996 to February 2020. The regressions from January 2010 to February 2020 work towards accounting for the impact, if any, of the Global Financial Crisis (GFC) of 2007 and 2008/2009. The absolute $t$-statistic from the regressions then produce significance level of each candidate factor in the analysis.

**Table 10: Pooled canonical correlations for asymptotic PC and significance of factor candidates**

| Canonical Variate | 1996-2009 | | | 2010-2020 | | | 1996-2020 | | |
|---|---|---|---|---|---|---|---|---|---|
| | Developing | Emerging | Developed | Developing | Emerging | Developed | Developing | Emerging | Developed |
| | Canonical Correlation | Canonical Correlation | Canonical Correlation | Canonical Correlation | Canonical Correlation | Canonical Correlation | Canonical Correlation | Canonical Correlation | Canonical Correlation |
| 1 | **0.91** | **0.94** | **0.99** | **0.91** | **0.92** | **0.97** | **0.81** | **0.89** | **0.94** |
| 2 | **0.78** | **0.75** | **0.84** | **0.83** | **0.88** | **0.93** | **0.77** | **0.82** | **0.87** |
| 3 | **0.62** | **0.63** | **0.76** | **0.72** | **0.85** | **0.76** | **0.72** | **0.78** | **0.70** |
| 4 | 0.34 | **0.49** | **0.63** | **0.54** | **0.71** | **0.73** | **0.64** | **0.67** | **0.68** |
| 5 | 0.25 | 0.34 | **0.58** | 0.42 | **0.63** | **0.67** | **0.46** | **0.52** | **0.66** |
| 6 | 0.21 | 0.31 | **0.45** | 0.37 | **0.51** | **0.55** | 0.36 | **0.48** | **0.59** |
| 7 | 0.16 | 0.28 | 0.30 | 0.22 | 0.38 | 0.41 | 0.37 | 0.37 | 0.42 |
| 8 | 0.09 | 0.21 | 0.18 | 0.17 | 0.31 | 0.34 | 0.26 | 0.31 | 0.39 |
| 9 | 0.07 | 0.12 | 0.11 | 0.09 | 0.25 | 0.26 | 0.28 | 0.25 | 0.24 |
| 10 | 0.02 | 0.08 | 0.05 | 0.00 | 0.17 | 0.13 | 0.16 | 0.12 | 0.19 |
| B. significance tests (t-stats) for factor candidates | | | | | | | | | |
| | t-stat | t-stat | t-stat | t-stat | t-stat | t-stat | t-stat | t-stat | t-stat |
| MKT | **2.23** | **3.56** | **5.67** | **2.57** | **3.82** | **3.25** | **2.04** | **3.22** | **3.18** |
| SMB | **1.97** | 1.80 | **4.37** | **3.44** | **2.37** | **2.19** | **1.99** | **3.34** | **5.26** |
| HML | **2.43** | **2.67** | **2.96** | **4.39** | **2.44** | **3.51** | **4.04** | **2.69** | **2.97** |
| CMA | 1.50 | 0.58 | **4.95** | 1.28 | 1.29 | **2.62** | 1.51 | 1.29 | **2.19** |
| RMW | **3.39** | **2.77** | **4.19** | **2.69** | **2.92** | **2.26** | **4.15** | **2.35** | **3.15** |
| DE | 0.96 | 0.36 | **2.69** | 1.44 | 1.36 | **2.91** | 1.22 | 1.47 | **2.39** |
| IML | 1.80 | **2.91** | 1.24 | **2.74** | **3.18** | 1.46 | 1.25 | **2.78** | 1.17 |
| UMD | **2.88** | 1.96 | **2.11** | **3.52** | **2.14** | **2.32** | **3.05** | **3.22** | **2.29** |
| PMU | 1.66 | 0.95 | 0.44 | 1.62 | **2.03** | 1.42 | 1.52 | 1.78 | 1.27 |
| PMN | **2.43** | **2.67** | 0.58 | **1.91** | **2.91** | 1.24 | 1.94 | 1.69 | 1.34 |
| DEI | 1.26 | **3.48** | **2.62** | 1.49 | **3.79** | 1.27 | 1.29 | **3.19** | 1.27 |
| UI | **2.29** | **3.38** | **2.11** | **3.22** | **3.69** | 1.32 | **3.13** | **3.55** | 1.63 |
| LIQ | **2.26** | **3.28** | **2.98** | **2.91** | **3.58** | **3.26** | **2.72** | **2.79** | **3.28** |
| REQ | 1.32 | 1.36 | **1.97** | 1.53 | 1.48 | 1.43 | 1.41 | 1.41 | 1.29 |
| ROL | 1.66 | 1.31 | 1.67 | 1.74 | **2.42** | 1.45 | 1.54 | **2.57** | 1.03 |
| VOL | **4.67** | **3.21** | **2.88** | **3.09** | **3.53** | **2.13** | **4.11** | **3.14** | **2.21** |
| MS | 1.62 | **2.39** | 0.07 | 1.16 | **2.61** | 1.08 | 1.07 | **2.49** | 1.45 |

| | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| AGR | 1.86 | **2.48** | 1.09 | **2.12** | **2.71** | 1.19 | 1.39 | **2.77** | 1.22 |
| CC | 1.81 | 1.67 | **3.79** | **1.97** | 1.81 | **4.12** | 1.57 | 1.26 | **3.18** |
| GTP | 1.73 | 1.44 | **3.84** | 1.28 | 1.84 | **4.19** | 0.90 | 1.54 | **2.82** |
| GDS | 1.69 | 1.47 | **2.97** | 1.25 | 1.38 | **3.23** | 1.03 | 1.33 | **3.09** |
| MTL | 1.61 | **2.48** | 1.23 | 1.47 | 1.55 | 1.34 | 1.44 | 1.50 | 1.54 |
| GI | 0.97 | **2.42** | **3.08** | **1.99** | **2.29** | **2.46** | 1.73 | **2.43** | **2.83** |
| OIL | **3.35** | **2.56** | 1.81 | **3.25** | **2.78** | **2.84** | **2.98** | **2.58** | **2.88** |
| TW$ | **5.13** | **2.69** | **3.49** | **4.23** | **2.24** | 1.81 | **3.75** | **2.51** | 1.21 |
| VX | 1.78 | **2.82** | **5.32** | 1.91 | **3.12** | **3.98** | 1.29 | **2.83** | **3.66** |

Notes: Table 11 detail canonical correlations and significance tests of the candidate risk factors in a pooled sample of developing, emerging, and developed equity markets. Panel A discloses the canonical correlations between the asymptotic PCs and the canonical variates, Significance of the canonical variates is presented using z-statistic values. Values in Panel A signified in bold indicate level of significance where $z$-statistics $\geq 2.0$. In Panel B, significant factors are noted in bold indicating a $t-$statistic greater than 2.0.

The sample of focus, developing equity markets, produces up to 11 significant candidate risk factors in the first subsample period, while the second subsample produces 15 significant risk factors. For the base period, developing equity markets register only 10 significant factors. This seems to contradict the picture portrayed in Panel A of Table 11 where the whole sample period registered an increase in the number of significant canonical variates. However, looking from the lens of individual country results reported in Table 10 there is an improved clarity that factors such as investment and debt-equity ratio factors struggle to systematically influence return variations in developing equity markets. It is also apparent that investors prefer persistency in the profit over predictability as evidenced by the PMN factor. These preliminary findings are not at odds with existing empirical evidence in developing equity markets. The evidence adduced by Charteris, Rwishema, and Chidede (2018), Zaremba et al. (2019), and Mosoeu and Kodongo (2020) support the presence of profitability premium in frontier and emerging equity markets but fails to find a role for value, size, and investments.

Results in Table 11 further suggest that only two of the global factors have a significant bearing on developing equity markets covariance returns matrix. However, while the two subsample periods register more than two important factors, when the whole period of the study is considered, only brent crude oil prices and trade-weighted dollar exchange rates register statistical significance. The table further exhibits that there are no substantial changes in the global macro variables that were significantly related to covariance matrix of returns in the post-GFC except for global stock market index proxied by MCSI return index.

However, when strictly considered from the aftermath of 2007/8 GFC, the variables begin to significantly show up in the covariance matrix of returns in the developing countries included in the study. Additionally, these results reaffirm the relationship already established in the individual country analysis. Majority of the markets in this category appeared to be

significantly influenced by the innovations in the global macroeconomic environment. The results hence possibly suggest that the aftermath of the GFC served as a catalyst for integration, where the returns in developing equity markets begun to significantly respond to the innovations in the global environment. For emerging and developed markets, the picture portrayed in Table 11 is not far-off evidence in the empirical literature.

The overarching objective underpinning the first phase of this study was to systematically identify the main drivers of observed returns in developing equity markets. Results provided in Tables 9, 10 and 11 reveal pertinent information and potential characteristics of the risk factors associated with expected returns in the sampled markets. The analysis thus far is alluding to the phenomenon that significant risk factors associated with return matrix may be related to the systematic volatility of returns and possibly commanding risk premium. The analyses have also established existence of a multivariate risk structure in developing equity markets. The pooled sample results provided in Table 11 which employs asymptotic PCA, and canonical correlations analysis provide an important opportunity to re-evaluate the potency and veracity of the factors found to influence returns variations at country level. This is specifically germane because asset pricing literature is replete with spurious or redundant risk factors. The analysis in Table 11 also provides another opportunity to determine common underlying drivers of returns in developing, emerging, and developed stock markets altogether.

Given the foregoing, can we conclude that $x$ number of factors significantly influence return generating process in the target sample of the study? Using the information provided in Table 11, we can deduce that about 10 of the 26 variables/factors influence returns variation in the developing equity markets. We can also, at this preliminary level, infer that developing equity markets are gradually integrating[28] with the global markets, and possibly with each other. The

[28] This is informed by the performance of the global macroeconomic variables, especially in the second subsample period.

impact of GFC, as can be deduced from Table 11, appears to have significant bearing on the observed improved integration. The successful candidate risk factors for developing equity markets that will move to the next stage of empirical analysis include market (MKT), size (SMB), value (HML), profitability (RMW), momentum (UMD), unanticipated inflation (UI), aggregate market volatility (VOL), aggregate liquidity (LIQ), returns on Brent crude oil (OIL) and returns on trade-weighted US dollar (TW$).

Although many studies in the developing country asset pricing literature (e.g., Blackburn and Cakici, 2017; Boamah, 2017; Bouri et al., 2017; De Groot et al., 2012; Zaremba et al., 2018; Zaremba and Maydybura, 2019; Zaremba et al., 2019) have investigated some of the factors identified here, to our knowledge, this study is the first to assemble a large group of factors and variables, and diligently combed through them to systematically ascertain their statistical and economic significance to equity prices in these markets. In addition, this study does not only test these factors based on prior knowledge established in studies elsewhere or within the markets of target but also allows room for any potential risk factor to be interrogated This is an important empirical contribution to the asset pricing literature in developing equity markets. In the next chapter, the study seeks to establish whether the factors identified in this chapter are priced (i.e., command a significant risk premium) in developing equity markets. For robustness checks, similar tests are performed with emerging and developed equity markets.

# CHAPTER 5

# EMPIRICAL IDENTIFICATION OF PRICED RISK FACTORS

## 5.1 Introduction

An important question so far unanswered by the analyses conducted in Chapter 4 is whether the factors found significantly related to the covariance matrices of returns command significant risk premiums. This question is more important because many empirical endeavours have resulted in factors with low ability to account for return variations and have been criticized[29] for inadvertently allowing factors with statistical appeal but limited economic significance.

This study has attempted to mitigate this shortcoming through the procedures in Chapter 4, which established some salient features about asset returns and candidate risk factors for developing equity markets. Having established the identities of factors, it is now important to establish whether the identified factors command a risk premium in developing equity markets. This is the task this chapter must now undertake.

## 5.2 Construction of Test portfolios

As already discussed, all stock price data are reported in US dollar terms, and stock returns calculated as the log difference between two consecutive stock prices as; $r_t = 100 \times [\ln(p_t) - \ln(p_{t-1})]$, where $r_t$ is the dollar stock return at time $t$, $p_t$ is the stock price at time t. Stocks with at least 5 consecutive months of zero returns are omitted from the sample. Portfolios are constructed from the firm characteristics with available data over the sample period using both equal-weighted and capitalization-weighted approaches. At the end of June each year, stocks

[29] Kelly et al. (2019), Bryzgalova (2015), Hsu and Kalesnik (2014) and Feng et al. (2020) among others firmly conclude that majority of the frequently researched asset pricing factors are spurious. Kelly et al. (2019) and Pukthuanthong et al. (2019) suggest that the inability of many studies to relate the factors to the covariance matrix of asset returns, resulting in many spurius risk factors.

are allocated to three equal-weight (EW) or capitalization-weighted portfolios using relevant firm characteristics.

Firms are also independently allocated to two size groups (small and big) using 10% and 90% of pooled market cap, respectively. For the cap-weighted portfolios, stocks are further independently allocated into two portfolios using $30^{th}$ and $70^{th}$ percentiles of the second sorting variables and returns calculated for the next twelve months beginning July of each year.

We impose a caveat in which portfolios are only constructed based on firm fundamental variables that pass the initial stage of factor identification procedure in Chapter 4. However, due to the importance of the capital structure decision, the debt-equity ratio is considered in test portfolio construction despite its lacklustre performance in the factor identification stage of the study. This decision has practical implications given that developing markets are still largely devoid of traded debt instruments, while at the same time, majority of the countries comprising developing equity markets actively participate in the international debt markets through the issuance of Eurobonds to finance capital intensive infrastructural projects (Bassett, 2017; Senga, Cassimon, and Essers, 2018). Furthermore, studies in developing markets document that firms only use short-term and expensive debt but rely heavily on equity for capital financing (Yartey, 2009). Further insight into the debt-equity financing mix is of particular significance, not only to the local firms domiciled in developing equity markets, but also critical for multinational firms willing to finance and expand their presence in these markets. It is against this backdrop that we evaluate portfolios formed on the debt-equity due to its practical implications on overall financing decisions of firms.

### 5.3 Preliminary Statistics

This section presents preliminary descriptions of the test portfolios and risk factors that satisfied the factor identification criteria undertaken in the previous section. There are 18 equal-

weighted and 24 capitalization-weighted test asset portfolios constructed on the five surviving firm fundamentals and one additional factor that includes size, book-to-market, operating profitability, liquidity, momentum, and debt-to-equity ratio. The analysis performed in this section includes descriptive statistics and correlation analysis of the candidate risk factors. We also test for autocorrelations for both the test asset returns and the candidate risk factors.

### 5.3.1 Descriptive behavior of the test portfolio returns

Table 13 details descriptive statistics while Table 14 details autocorrelation functions of 18 EW and 24 VW portfolios constructed on six firm fundamental factors in developing equity markets.

Examination of the results in Table 12 reveals that these series do not exhibit a normal distribution. All the skewness coefficients are either above or below the threshold value of 0. A similar picture is also observed in kurtosis values which are much higher than the normal value of 3, indicating excess kurtosis. The p-values of JB tests are all significant at 1% level, further rejecting the hypothesis of normality. Panel A of Table 12 reveals that EW Book-Market (BM) portfolios earn higher average returns compared to their VW counterparts. Equally, EW BM portfolios earn higher risk-adjusted average returns as revealed by the Sharpe ratios. Profitability and investment portfolios also portray a picture consistent with the BM portfolios.

Liquidity portfolios display the highest average monthly returns for both equal weighted and size weighted portfolios. Panel C of Table A indicates that equal-weighted liquidity portfolios earned a maximum of 1.45% risk-adjusted returns over the period of the study. Momentum portfolios also produce higher returns across the panel for both capitalization-weighted and equal-weighted portfolios. Panel D shows the highest capitalization-weighted portfolio return belongs to the momentum group. Average returns displayed in Table 10 here closely mirrors

comprehensive equal-weighted and value-weighted anomaly portfolio returns in Table 3 of Zaremba, et al. (2019) and Table 3 panels A and B in Boamah (2017). The two authors examined risk-return relationships in frontier equity markets, where the former correctly replicated 167 anomalies in Islamic stocks, while the latter examined size, value, and momentum anomalies in African frontier equity markets.

STD in Table 12 is associated with historical return volatility and measures total risk of the portfolios over the period of the study. Given that STD constitutes risk, higher values are not desirable as it signifies a high degree of return variability and deviations from the expected returns.

The Sharpe ratios in Table 12 for all the panels are not far off each other, indicating that developing equity markets still offer significant abnormal risk-adjusted returns.

In terms of distribution asymmetry, results displayed in Table 12 are consistent with empirical evidence in developing, and emerging equity markets return behaviours. Harvey and Siddique (2000), for instance, observed that significant positive skewness influences investors to hold on to stocks whose overall contribution to their portfolios may be negative. Booth and Smith (1987), on the other hand, found that larger skewness and kurtosis coefficients are more prevalent with smaller firms. Langlois (2020) in a recent study presents evidence that firms with extreme and idiosyncratic skewness tend to be volatile, and that higher skewness is conspicuous in small growth stocks.

Higher distribution moments, as opposed to the conventional mean-variance criteria, have, in the recent past emerged in asset pricing literature see (Ebert and Hilpert, 2019; Ho and Cheung, 1991; Kane, 1982). Ebert and Hilpert (2019), in particular, established that majority of institutional and even individual investors prefer chartists or technical analysis in making portfolio allocation decisions. The authors opine that technical analyst's primary tool of

prediction is based on historical price behaviours, and that skewness is the most preferred statistical moment because of its lottery-like characteristics. In a comprehensive investigation of portfolio selection patterns among investors in Latin America, Prakash, Chang, and Pactwa (2003) document results corroborating the evidence that investors trade expected return of portfolios for skewness. Moreover, among the early investigators of international portfolio allocations patterns, especially to markets considered less developed, Harvey (2000) suggest that skewness may be a leading contributor to portfolio allocation in international markets, but warn that investors need to be wary of skewness, and instead consider co-skewness as the leading metric in making portfolio allocation decisions, particularly in less developed markets.

Extant empirical asset pricing literature argues that quadratic nature of the investor utility functions significantly contributes to preference of skewness as a statistical moment over mean and variance (Ebert and Hilpert, 2019; Kun, 2017; Zhen, 2020). The evidence in Table 12 speaks to these empirical regularities. Autocorrelation functions reported across the panels of Table 12 do not display any worrisome picture for persistent serial correlation in returns. The results in Table 12 generally reveal presence of positive first-order autocorrelation, in almost all the portfolios included in this study. Autocorrelation functions of the portfolio returns are significant for the first lag, except for liquidity portfolios and to some extent momentum portfolios which exhibit significant autocorrelation functions for up to $6^{th}$ lag.

Return autocorrelation is a significant component of return predictability and is associated with market efficiency (Chelley-Steeley and Steeley, 2014). Chelley-Steeley and Steeley (2014) note that securities that fail to impound market-wide news into their prices often cause autocorrelation when included in a portfolio. Ngo and Jory (2008) establish that less developed markets experience strong serial correlation in their stock returns. They connect this to information inefficiency, implying that return autocorrelation necessitates return predictability.

**Table 11: Descriptive Statistics for the Test Portfolios**

| | Equally Weighted | | | Value-weighted | | | |
|---|---|---|---|---|---|---|---|
| | *P*1 | *P*2 | *P*3 | *P*1 | *P2* | *P3* | *P4* |
| *Panel A: Book-Market portfolios* | | | | | | | |
| Mean | 1.36 | 0.87 | 1.96 | 0.45 | 0.23 | 0.71 | 1.11 |
| STD | 1.86 | 3.46 | 1.76 | 2.79 | 1.79 | 2.52 | 2.58 |
| SR | 0.73 | 0.25 | 1.11 | 0.16 | 0.13 | 0.28 | 0.43 |
| Skew | 0.40 | -0.46 | 0.43 | -0.65 | 0.75 | 0.54 | -0.70 |
| Kurt | 6.66 | 4.91 | 5.53 | 3.51 | 2.54 | 5.20 | 2.98 |
| JB | 48.88 | 65.12 | 68.73 | 47.84 | 31.82 | 57.69 | 39.23 |
| P-value of JB | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.02 | 0.00 |
| *Panel B: Operating Profitability portfolios* | | | | | | | |
| Mean | 0.88 | 2.94 | 1.61 | 0.43 | 1.17 | 0.88 | 0.52 |
| STD | 2.52 | 4.67 | 2.38 | 3.77 | 2.42 | 3.39 | 3.48 |
| SR | 0.35 | 0.63 | 0.68 | 0.11 | 0.48 | 0.26 | 0.15 |
| Skew | -0.29 | -0.45 | 0.37 | 0.62 | -0.72 | 0.34 | 0.67 |
| Kurt | 2.02 | 2.45 | 0.86 | 1.64 | 0.5 | 1.79 | 1.33 |
| JB | 42.29 | 14.56 | 18.67 | 21.52 | 13.46 | 24.31 | 27.40 |
| P-value of JB | 0.09 | 0.01 | 0.06 | 0.01 | 0.00 | 0.09 | 0.01 |
| *Panel C: Liquidity Portfolios* | | | | | | | |
| Mean | 1.33 | 4.89 | 2.54 | 0.41 | 1.12 | 0.84 | 1.02 |
| STD | 3.05 | 3.38 | 5.33 | 5.44 | 3.21 | 3.82 | 3.76 |
| SR | 0.44 | 1.45 | 0.47 | 0.08 | 0.35 | 0.22 | 0.27 |
| Skew | -1.34 | -0.65 | -1.77 | -2.02 | -1.01 | -1.38 | -1.23 |
| Kurt | 0.19 | 0.17 | 0.48 | 0.09 | 0.34 | 0.26 | 0.41 |
| JB | 2.56 | 2.59 | 2.72 | 1.88 | 2.16 | 2.49 | 2.02 |
| P-value of JB | 0.08 | 0.01 | 0.00 | 0.01 | 0.00 | 0.08 | 0.00 |
| *Panel D: Momentum Portfolios* | | | | | | | |
| Mean | 2.31 | 2.85 | 1.47 | 1.39 | 2.07 | 2.81 | 1.84 |
| STD | 3.22 | 1.39 | 2.97 | 3.82 | 3.68 | 4.10 | 4.35 |
| SR | 0.72 | 0.61 | 0.49 | 0.36 | 0.56 | 0.68 | 0.42 |
| Skew | -1.17 | -0.64 | -2.05 | -2.19 | -1.24 | -1.46 | -1.5 |
| Kurt | 0.07 | 0.12 | 0.34 | 0.06 | 0.24 | 0.20 | 0.29 |
| JB | 0.12 | 3.79 | 5.98 | 3.35 | 3.86 | 3.36 | 3.61 |
| P-value of JB | 0.09 | 0.01 | 0.00 | 0.01 | 0.00 | 0.08 | 0.00 |
| *Panel E: Debt-to-Equity Portfolios* | | | | | | | |
| Mean | 0.36 | 0.81 | 1.40 | 0.37 | 1.02 | 0.77 | 1.75 |
| STD | 6.56 | 5.51 | 5.81 | 6.83 | 5.54 | 6.23 | 5.63 |
| SR | 0.05 | 0.15 | 0.24 | 0.05 | 0.18 | 0.12 | 0.31 |
| Skew | 1.45 | -0.5 | -0.49 | 0.54 | 0.62 | 0.30 | 0.58 |
| Kurt | -2.42 | -4.29 | -4.45 | 3.81 | -2.8 | 3.69 | -2.87 |
| JB | 14.35 | 25.38 | 26.30 | 22.56 | 16.58 | 22.20 | 17.00 |
| P-value of JB | 0.53 | 0.05 | 0.15 | 0.07 | 0.01 | 0.25 | 0.02 |

Notes: This table presents preliminary analysis of equal-weighted and value-weighted portfolios formed on book-to-equity (BM), operating profitability, liquidity, momentum, and investment. At the end of each June, stocks are allocated into three equal weight and into two size-weight portfolios using lower $30^{th}$ percentile, percentile, and upper $70^{th}$ percentiles of the sorting variables. Value weight portfolios are sorts on two small portfolios and two big portfolios. To calculate excess returns, a one-month US treasury bill rate obtained from Kenneth French data library is subtracted from the returns of each portfolio. Summary statistics conducted in this study include mean, standard deviation (STD), Sharpe ratio (Sharpe R), skewness (Skew), and kurtosis (Kurt).

Nonsynchronous trading is also believed to be a major contributor to return autocorrelation and returns predictability (Rahman, Lee, and Shamsuddin, 2017). Rahman et al. (2017) document that factors such as automation of trading, volatility of returns, liquidity, and level of development contribute to nonsynchronous trading. However, as demonstrated by Lo and MacKinlay (1990) and elaborated by Chelley-Steeley and Steeley (2014), nonsynchronous trading does not account for the entire portfolio return autocorrelation. Other factors, such as thin trading, low number of firms trading, and included in a particular portfolio, time-varying expected returns, non-trading, stale limit orders, or market-maker trading strategies also contribute to return autocorrelation. If taken that small number of securities in a portfolio significantly contribute to return autocorrelation, then we expect to see higher autocorrelation for the returns of developing equity market portfolios included in this study, which is not the case here, as already observed.

The role of liquidity in market efficiency and return predictability is well documented in finance literature. Empirical finance attribute illiquidity to market inefficiency which attracts significant risk premium in financial markets (Chordia et al., 2008). In an inefficient market, stock prices do not fully reflect relevant information about the stocks and may lead to mispricing of such securities. In this regard, the persistence shown by liquidity stocks in Table 13 is therefore, not surprising. The results possibly indicate the influence of liquidity on the return generating process in the developing equity markets. Developing equity markets, and to a large extent, emerging equity markets have been reported to display persistent portfolio return autocorrelation as a result of low volume of trade (Smith and Dyakova, 2014). For instance, in an attempt to disentangle return behaviour in the Russian stock market, Kinnunen (2013) documents that high degree of return predictability in Russia is induced by high order return autocorrelation. Kinnunen further detail that persistence in return autocorrelation varies with the level of information available in the market.

**Table 12: Return autocorrelations functions**

| | Equally Weighted | | | Value-weighted (small and big portfolios) | | | |
|---|---|---|---|---|---|---|---|
| | *P1* | *P2* | *P3* | *P1* | *P2* | *P3* | *P4* |
| *Panel A: Book-Market portfolios* | | | | | | | |
| $\rho_1$ | **0.25**** | **0.27**** | **0.26**** | **0.21**** | **0.26**** | **0.29**** | **0.27**** |
| $\rho_2$ | **0.18***** | 0.08 | **0.19***** | 0.09 | **0.14***** | **0.12***** | **0.15***** |
| $\rho_6$ | 0.09 | 0.06 | 0.09 | 0.05 | 0.08 | 0.07 | 0.08 |
| $\rho_{13}$ | 0.06 | 0.03 | 0.07 | 0.03 | 0.02 | 0.10 | 0.05 |
| $\rho_{22}$ | 0.02 | 0.01 | 0.05 | -0.02 | -0.03 | 0.04 | -0.01 |
| *Panel B: Operating Profitability portfolios* | | | | | | | |
| $\rho_1$ | **0.15***** | **0.18***** | **0.15***** | **0.28**** | **0.21**** | **0.24**** | **0.20**** |
| $\rho_2$ | 0.08 | **0.10***** | 0.06 | 0.06 | **0.16***** | **0.10***** | **0.13***** |
| $\rho_6$ | **0.12***** | **0.10***** | **0.11***** | 0.08 | **0.13***** | 0.07 | **0.14***** |
| $\rho_{13}$ | 0.04 | 0.00 | -0.01 | 0.05 | 0.06 | 0.07 | 0.06 |
| $\rho_{22}$ | -0.04 | -0.04 | -0.04 | 0.03 | 0.01 | 0.04 | 0.00 |
| *Panel C: Liquidity Portfolios* | | | | | | | |
| $\rho_1$ | **0.26**** | **0.26**** | **0.27**** | **0.21**** | **0.60*** | **0.30**** | **0.68*** |
| $\rho_2$ | **0.17***** | **0.19***** | **0.18***** | **0.15***** | **0.21**** | **0.12***** | **0.47*** |
| $\rho_6$ | **0.16***** | **0.15***** | **0.15***** | **0.11***** | 0.03 | **0.10***** | 0.09 |
| $\rho_{13}$ | 0.04 | 0.05 | 0.04 | 0.04 | 0.02 | 0.09 | 0.06 |
| $\rho_{22}$ | 0.03 | 0.03 | 0.02 | 0.03 | 0.00 | 0.07 | 0.01 |
| *Panel D: Momentum Portfolios* | | | | | | | |
| $\rho_1$ | **0.31**** | **0.52*** | **0.47*** | **0.39*** | **0.32**** | **0.50*** | **0.45*** |
| $\rho_2$ | **0.19***** | **0.15***** | **0.33**** | **0.28**** | **0.18***** | **0.18***** | **0.13***** |
| $\rho_6$ | 0.03 | 0.08 | **0.11***** | 0.06 | 0.08 | 0.09 | 0.07 |
| $\rho_{13}$ | 0.09 | -0.04 | 0.09 | 0.04 | 0.06 | 0.06 | 0.06 |
| $\rho_{22}$ | 0.09 | 0.08 | 0.01 | 0.07 | 0.05 | 0.03 | 0.02 |
| *Panel E: Debt-to-Equity Portfolios* | | | | | | | |
| $\rho_1$ | 0.09 | 0.07 | 0.06 | **0.11***** | **0.13***** | 0.06 | 0.09 |
| $\rho_2$ | 0.08 | 0.05 | 0.03 | 0.08 | 0.08 | 0.04 | 0.08 |
| $\rho_6$ | 0.03 | 0.03 | 0.03 | 0.06 | -0.09 | 0.08 | 0.06 |
| $\rho_{13}$ | -0.10 | -0.04 | 0.01 | 0.04 | 0.07 | 0.07 | 0.04 |
| $\rho_{22}$ | 0.08 | 0.08 | -0.10 | 0.07 | 0.05 | 0.04 | 0.07 |

This table presents autocorrelation functions of equal-weighted and value-weighted portfolios formed on book-to-equity (BM), operating profitability, liquidity, momentum, and investment. At the end of each June, stocks are allocated into three equal weight and into three size-weight portfolios using lower 30$^{th}$ percentile, middle 40$^{th}$ percentile, and upper 70$^{th}$ percentiles of the sorting variables. Value weight portfolios are sorts on two small portfolios and two big portfolios using 30$^{th}$ and 70$^{th}$ percentiles of the sorting variables. To calculate excess returns, a one-month US treasury bill rate obtained from Kenneth French data library is subtracted from the returns of each portfolio.

### 5.3.2 Descriptive behavior of the candidate risk factors

Table 14 documents descriptive analysis and autocorrelation functions of the candidate risk factors considered for empirical asset pricing test in this study. Given the metrics already discussed in the section dealing with summary statistics for test asset portfolios, all the candidate risk factors in this study display a non-normally distributed series. Standard deviation (STD) values in Table 14 indicate that factors constructed on firm characteristics are highly volatile compared to macroeconomic-based factors.

**Table 13: Descriptive Statistics for the 10 Candidate Risk Factors**

| **Panel A: Summary Statistics** | | | | | | |
|---|---|---|---|---|---|---|
| | Mean | STD | Skew | Kurt | JB | Obs |
| MKT | 0,21 | 0,10 | -0,18 | 3,94 | 5,87‡ | 290 |
| SMB | 0,38 | 0,06 | -0,94 | 7,09 | 4,14‡ | 290 |
| HML | 0,90 | 0,05 | 0,19 | 1,38 | 8,64‡ | 290 |
| RMW | 1,36 | 0,09 | 0,21 | 2,19 | 16,51‡ | 290 |
| UMD | 1,55 | 0,10 | -0,85 | 4,52 | 8,14‡ | 290 |
| UI | 1,60 | 0,05 | -0,29 | 4,68 | 9,25‡ | 290 |
| LIQ | 0,36 | 0,03 | -0,13 | 2,40 | 9,53‡ | 290 |
| VOL | -1,07 | 0,05 | 0,15 | 8,18 | 10,37‡ | 290 |
| OIL | 0,99 | 0,04 | -0,27 | 1,45 | 12,59‡ | 290 |
| TW$ | 0,07 | 0,06 | -0,08 | 3,06 | 12,87‡ | 290 |

| **Panel B: Autocorrelation functions** | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | $\rho_1$ | $\rho_2$ | $\rho_3$ | $\rho_4$ | $\rho_5$ | $\rho_6$ | $\rho_{12}$ | $\rho_{24}$ |
| MKT | 0,22$^s$ | 0,08 | 0,13$^s$ | 0,01 | -0,05 | -0,09 | -0,03 | 0,01 |
| SMB | 0,07 | 0,04 | 0,05 | -0,02 | -0,01 | -0,01 | -0,02 | -0,04 |
| HML | 0,21$^s$ | 0,16$^s$ | 0,18$^s$ | 0,07 | 0,06 | 0,04 | -0,11 | -0,08 |
| RMW | 0,14$^s$ | -0,07 | 0,02 | -0,08 | 0,06 | 0,08 | -0,01 | -0,06 |
| UMD | 0,29$^s$ | -0,11 | 0,05 | 0,05 | 0,01 | -0,11 | 0,06 | -0,07 |
| UI | 0,34$^s$ | 0,22$^s$ | 0,18$^s$ | 0,14$^s$ | 0,09 | 0,07 | -0,26 | 0,04 |
| LIQ | 0,59$^s$ | 0,33$^s$ | 0,16$^s$ | 0,04 | -0,12 | -0,20 | -0,02 | 0,01 |
| VOL | -0,19$^s$ | 0,08 | 0,02 | 0,05 | -0,02 | -0,09 | -0,13 | -0,02 |
| OIL | 0,22$^s$ | 0,09 | 0,02 | -0,07 | -0,07 | -0,07 | -0,05 | -0,08 |
| TW$ | 0,33$^s$ | 0,13$^s$ | 0,09 | 0,16 | 0,08 | 0,06 | -0,07 | 0,02 |

‡ Indicate that Jarque-Bera coefficient of the candidate risk factors is statistically significant at 1% and 5% levels. $^s$ Indicate that autocorrelation functions of the candidate risk factors are statistically different from zero. STD is the standard deviation of the candidate risk factor, a measure of volatility. Measures of normality include Skew, Kurt, JB are skewness, kurtosis, and Jarque-Bera Coefficients, respectively. Obs is the short form of the observation, the 290 number of months (1996:1 to 2020:2) included in the analysis. MKT is the market excess return of the market which encompasses pooled sample of market returns of all the stock indices included in the study expressed in US dollar less one-month US Treasury bills. SMB is the difference between the pooled average returns of big market capitalization firms. HML is the difference between the pooled average returns of high and low book value of the market firms. RMW is the difference between the pooled average returns of robust and pooled average returns of week operating profitability firms. Momentum factor, UMD (up minus down) is constructed using the procedure provided by Skočir and Lončarski (2018a). Portfolios are formed at the end of month $t-1$, where the lagged momentum return is cumulative return of stock $i$ for month $t-12$ to

month $t-2$. Breakpoints are the bottom 30% (losers, D), middle 40% (Middle, M), and top 30% (Up, U) of the lagged momentum return in the two size groups of the pooled sample. Domestic macroeconomic variables are UI (unanticipated inflation), LIQ (aggregate liquidity), and VOL (aggregated market returns volatility). Global macroeconomic variables are OIL (return on crude oil prices), and TW$ (US dollar broad trade-weighted exchange Index.

Results in Table 14 Panel A details descriptive statistics for the five factors constructed on firm characteristic variables including market factor and the five macroeconomic variables that were successful in the factor identification phase of this empirical analysis. Statistical moments in Panel A include mean, standard deviation denoted as STD, skewness, kurtosis and Jarque-Bera statistics. According to the Table, firm characteristic variables including market factor largely exhibit higher positive mean returns over the period of the study. The momentum factor UMD outperforms the firm level factors by producing a monthly return of 1.55% over the sample period. RMW-gross profitability factor reports the second highest positive mean returns at 1.36%, followed at a distant by the value factor (HML) at 0.90%. STDs results for momentum, market, and profitability factors indicate that the factors exhibit higher levels of variability. The Jarque-Bera statistics are all large and significant at 1% level again suggesting non-normality.

The autocorrelation functions reported in Table 14 however do not indicate that serial correlation is not a critical concern for this study: the first-order autocorrelation function is generally statistically different from zero for most of the variables in the analysis. Only UI produces significant serial correlation up to the fourth lag.

### 5.3.2 Correlation Analysis

Deciphering the associations between pairs of independent variables provides an opportunity to uncover the statistical relationship between the variables. Correlations also provide a preliminary and cursory view of the bivariate relations between each of the candidate risk factors and is instrumental for model selection and parameter estimates.

As has been highlighted, the information presented in Table 15 is crucial for model identification, specification, and economic interpretations of the relationship between the

variables of interest. Series that are highly statistically related may suggest a common underlying phenomenon, or identical time series data generating process. Such series should not be considered in the same regression equation due to a possible multicollinearity. Coupled with heteroskedasticity and autocorrelation inherently present in economic and financial data series, multicollinearity, if left unaddressed, may result in biased inferences.

According to Table 15, majority of the variables included in this study display moderately weak linear relationships. The highest significant correlation can be observed between excess market returns factor and momentum factor at -0.56. Excess return of the market factor produces slightly higher correlations with at least four of the candidate risk factors, namely size, momentum, aggregate liquidity, and unanticipated inflation. The negative relationship observed between MKT and UI has theoretical implications. Expected inflation, though has yielded mixed empirical evidence in its relationship with stock returns generally, theoretically, the inverse relationship depicted between MKT and inflation permits the empirical relationship portrayed in Table 15.

**Table 14: Correlation Matrix for the Candidate Risk Factors**

| | MKT | SMB | HML | RMW | UMD | UI | LIQ | VOL | OIL |
|---|---|---|---|---|---|---|---|---|---|
| SMB | **-0,47** | | | | | | | | |
| HML | **0,12** | **-0,17** | | | | | | | |
| RMW | **-0,14** | -0,07 | **0,28** | | | | | | |
| UMD | **-0,56** | **-0,37** | **0,38** | 0,14 | | | | | |
| UI | **-0,55** | -0,11 | -0,12 | 0,02 | -0,12 | | | | |
| LIQ | **-0,41** | **0,27** | **-0,38** | **0,23** | -0,16 | 0,22 | | | |
| VOL | **0,14** | **-0,37** | **0,28** | **0,29** | **0,31** | **0,38** | 0,14 | | |
| OIL | **-0,17** | **0,39** | **-0,38** | 0,09 | -0,16 | 0,05 | 0,01 | **0,39** | |
| TW$ | **0,14** | **0,22** | -0,11 | 0,10 | -0,11 | **-0,18** | **-0,23** | **-0,23** | **0,15** |

This table provides statistical relationship between thirteen variables that were found to exhibit significant relationship with systematic volatility of returns in developing equity markets. Figures in bold indicate the statistical significance of the relationship between two variables.

Size, operating profitability, and momentum all provide significant negative relationship with the excess market return (MKT). These results are consistent with empirical evidence observed in Zaremba et al. (2019), who establish that excess return of the market has a negative but

significant relationship with size, profitability, and momentum. The authors also find similar evidence regarding the relationship between excess return of the market and value factor (HML) in frontier equity markets.

### 5.4 Are the Factors Priced?

The empirical starting point follows the convention established in asset pricing studies where we estimate the beta coefficients, then test if the betas are statistically distinguishable from zero. We follow the tradition for two reasons: first, there is sizeable empirical evidence supporting the simple regression models such as two-pass regression advanced by Fama and MacBeth (1973). Evidence suggests that the procedure is considered simple and accurate by many asset pricing researchers (see, for example, Pukthuanthong et al. (2019); second, we implement Fama and MacBeth (1973) two-pass regression procedure as the first model to determine if the incoming factors are significantly related to the systematic volatility of returns in the developing equity markets, priced, and actually command significant risk premium.

We first run multiple regression using each of the EW and VW portfolios on the surviving factors and extract the resulting OLS betas. Typically, the second pass of FM regression involves running a multiperiod cross-section regression using the extracted betas as the new regressor variables on the portfolios. For this study, this would involve running a cross-sectional regression with the extracted betas as the independent regressors on the EW and VW portfolios. However, there have been numerous concerns raised about the possibility of estimating the second pass regression with errors emanating from the first pass regression, thus distorting the resulting coefficients of beta. The so-called Errors-in-Variables (EIV) problem presents a gigantic setback for estimating FM regressions. To counter the problem, researchers have devised innovative ways to ensure that the second pass regression does not underestimate or overestimate the price of risk (gammas).

One of earlier attempts to solve the EIV problem was presented by Shanken (1992), who proposed using a modified two-pass regression by deriving an asymptotic distribution of the cross-section regression estimator that is generated by the portfolio returns and pre-specified factors. Another attempt is an approach by Kim (1995) who proposes the incorporation of information extracted from the relationship between the measurement errors variance and the idiosyncratic error variance into a maximum likelihood estimation. For this study, we implement a solution employed by Pukthuanthong et al. (2019) who perform double sorting criteria using the betas extracted from the OLS first pass regression to form test portfolios for the second pass regression. Their approach has the ability to minimize errors associated with the first pass regression into the second pass regression.

Thus, following Pukthuanthong et al (2019), we double sort portfolios to address the potential EIV problem in our FM estimations. Specifically, stocks are sorted into 5 portfolios using market capitalization. Then, using the beta associated with the first factor in the first pass regression, the stocks are further sorted into two portfolios resulting in 10 size-MKT$\beta$ portfolios. The same procedure is repeated to independently sort stocks for all the other four factors used to sort test portfolios for the first pass regression. When this process is completed, we take equal-weighted average of each of the factor betas and assign them to each portfolio within that group. The second pass regression thus uses the new portfolios formed on the intersection between the successful factor-beta and size variable.

To ensure that the resulting standard errors, $p$-values, and $t$-statistics are free from autocorrelation and heteroskedasticity biases, the standard errors are adjusted using Newey and West (1987) procedure. Besides, as a robustness check, we split the sample into two subsample periods and the baseline sample which covers the entire study period. The first model runs the sample period from January 1996 to December 2009, the second model is implemented from

January 2010 to February 2020, while the baseline model runs the entire sample period, from January 1996 to February 2020. This approach mitigates potential problems of structural breaks and establishes if the Global Financial Crisis of 2007 to 2009 had any significant impacts on the structure of risk pricing in developing equity markets.

Although FM regression is adequate in estimating the price of risk in this study, we further conduct a Generalized Method of Moments (GMM)-type regressions as a robustness check to completely ascertain those econometric problems, such as endogeneity arising from the close relationship between the determinant factors and the test portfolios. This is also performed to ensure that simultaneity bias does not pose any significant influence on the estimated risk premia. GMM is preferred for its flexibility to permit estimation of model parameters without imposing strong assumptions on the stochastic properties of the variables. Furthermore, GMM is robust to endogeneity, heteroskedasticity, and autocorrelation problems commonly encountered in financial time series data.

### 5.4.1 Summary statistics of beta loadings

As indicated earlier, we begin by first using the 18 and 24 portfolios as dependent variables on the surviving risk factors and extract their average OLS beta estimates, then using the betas as the independent variables in the second pass regression. Table 16 documents the point estimates of the extracted betas. Results indicate that loadings on the momentum factor are very volatile and negatively skewed. None of the factor loadings presented in the table are normally distributed: however, the coefficients of skewness and kurtosis are not as pronounced as those in Table 14 However, this does not pose a serious problem for our parameter estimates provided that the residuals are normally distributed. Further, we adjust standard errors in both the FM and GMM regressions using Newey and West (1987) adjustment with six lags.

**Table 15: Summary Statistics for candidate factor betas**

| | Developing Markets | | | | Emerging Markets | | | | Developed Markets | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Mean | SD | Skew | Kurtosis | Mean | SD | Skew | Kurtosis | Mean | SD | Skew | Kurtosis |
| MKT | 0,78 | 0,13 | 0,25 | 1,53 | 0,67 | 0,90 | 0,29 | 0,73 | 1,14 | 1,11 | 0,06 | 0,63 |
| SMB | -0,69 | 0,43 | -0,63 | 1,18 | 0,90 | 1,20 | -0,64 | -0,11 | 0,77 | 1,84 | -0,08 | -0,84 |
| HML | 0,85 | 0,44 | 0,93 | 0,80 | -1,15 | 1,54 | 0,79 | 1,04 | 0,72 | 1,04 | -0,12 | 1,01 |
| CMA | | | | | | | | | 0,92 | 0,77 | 0,04 | -1,12 |
| RMW | 1,19 | 0,64 | -0,97 | 1,13 | -0,71 | 0,94 | -0,40 | 1,24 | 0,79 | 1,10 | -0,12 | 0,21 |
| DE | | | | | | | | | -0,88 | 1,03 | 0,10 | -1,37 |
| IML | | | | | -0,72 | 0,96 | 0,38 | -1,35 | | | | |
| UMD | 1,01 | 1,99 | -0,69 | -0,57 | 0,92 | 1,23 | -0,72 | 0,91 | -0,81 | 0,80 | -0,09 | 0,64 |
| DEI | | | | | 0,39 | 0,52 | 0,17 | 1,61 | | | | |
| UI | -0,80 | 0,39 | -0,18 | -0,57 | -0,85 | 1,13 | -0,38 | -1,57 | | | | |
| LIQ | -0,79 | 0,54 | -0,15 | -0,80 | 0,76 | 1,02 | -0,36 | 1,52 | 1,14 | 1,15 | 0,08 | 0,84 |
| ROL | | | | | 0,46 | 0,61 | 0,31 | -0,90 | | | | |
| VOL | -1,63 | 0,51 | -0,12 | 0,78 | -0,81 | 1,08 | -0,94 | -1,50 | 0,75 | 0,77 | -0,20 | -0,78 |
| MS | | | | | 0,30 | 0,41 | 0,19 | 1,11 | | | | |
| AGR | | | | | 0,56 | 0,74 | 0,34 | 1,15 | | | | |
| CC | | | | | | | | | -1,44 | 1,11 | 0,05 | 1,47 |
| GTP | | | | | | | | | 0,47 | 0,99 | -0,23 | 0,94 |
| GDS | | | | | | | | | 1,13 | 1,08 | 0,47 | -1,20 |
| GI | | | | | 0,52 | 0,70 | 0,38 | 0,97 | 0,86 | 0,99 | -0,05 | 0,73 |
| OIL | 0,73 | 0,26 | 0,90 | 0,49 | 0,85 | 1,14 | 0,51 | 1,18 | 0,99 | 1,01 | 0,09 | 0,88 |
| TW$ | -1,80 | 0,52 | -0,94 | -0,94 | -1,11 | 1,48 | -0,83 | 0,95 | | | | |
| VX | | | | | -0,50 | 0,67 | -0,27 | -1,33 | -1,39 | 1,28 | -0,04 | -0,68 |

This table provides summary statistics for beta loadings on the factors that pass factor identification phase for each of the three markets. Betas (OLS slope coefficients) are computed for each of the 18 and 24 portfolios in multiple regression of portfolio's monthly return on monthly factor realizations, using 290 months of observations for each portfolio. Also included in the table are summary statistics such as mean, median, standard deviation (STD), Skewness, and kurtosis. Blank spaces in each of the market categories belong to factor which did not pass the factor identification process for that specific market. There are 10 candidate risk factors for developing equity markets, while emerging and developed markets respectively have 17 and 15 candidate risk factors

**Table 16: Estimated price of risk for the successful candidates in developing equity markets**

| | Model 1: No EIV correction | | | | | | Model 2: EIV Correction | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | 1996 to 2009 | | 2010 to 2020 | | 1996 to 2020 | | 1996 to 2009 | | 2010 to 2020 | | 1996 to 2020 | |
| | $\lambda_i$ | $t-$stat | $\lambda_i$ | $t-$stat | $\lambda_i$ | $t-$stat | $\lambda_i$ | $t-$stat | $\lambda_i$ | $t-$stat | $\lambda_i$ | $t-$stat |
| Constant | 0,824 | ***6,826*** | 1,592 | ***5,768*** | 0,656 | ***4,184*** | 0,429 | ***4,060*** | 0,272 | **2,019** | 1,630 | ***3,305*** |
| MKT | 0,128 | ***4,016*** | 0,128 | ***3,888*** | -0,096 | **-2,592** | 0,045 | **2,847** | -0,059 | ***-3,361*** | 0,034 | **2,192** |
| SMB | -0,016 | -1,792 | -0,064 | -1,888 | -0,592 | -1,264 | -0,006 | -0,824 | -0,029 | -0,661 | -0,907 | -0,581 |
| HML | 0,064 | 1,472 | 0,064 | **2,032** | 0,416 | ***3,472*** | 0,022 | 1,517 | 0,029 | **2,111** | 0,146 | ***3,677*** |
| RMW | 0,296 | 1,504 | -0,960 | ***-3,304*** | -0,066 | **-2,488** | -0,454 | -1,612 | -1,362 | **-2,206** | -0,582 | **-2,684** |
| UMD | -0,760 | ***-3,488*** | 1,824 | **2,152** | 0,384 | ***3,536*** | -0,616 | **-2,604** | -0,839 | **2,503** | 0,834 | ***4,707*** |
| UI | -0,928 | -1,792 | 0,312 | **2,044** | -0,896 | -1.841 | 0,025 | 1,664 | 0,035 | **2.011** | 0,314 | 1,952 |
| LIQ | -0,408 | -1,216 | -0,248 | -1,240 | -0,176 | -0,160 | -0,143 | -0,559 | 0,574 | -0,084 | 0,762 | -1,736 |
| VOL | -0,496 | ***-3,344*** | -0,501 | **-2,544** | -0,368 | -1,696 | -0,174 | **-2,538** | 0,046 | -0,890 | -2,129 | ***-5,780*** |
| OIL | 0,640 | **2,094** | 0,864 | ***3,344*** | 0,040 | **2,240** | 0,224 | 1,945 | 0,397 | **2,170** | 0,364 | 1,630 |
| TW$ | -0,190 | -1,488 | -0,704 | -1,024 | -0,416 | **-2,672** | -0,066 | -1,604 | -0,324 | **-2,358** | -0,146 | -1,929 |
| Lag 1 | -1,512 | **-2,872** | -0,512 | **-2,576** | -0,024 | -1,712 | -0,529 | -1,321 | -0,236 | -0,902 | -0,708 | -1,788 |
| Lag 12 | -0,672 | ***-3,018*** | -0,334 | **-2,891** | -0,194 | ***-3,920*** | -0,235 | -1,881 | -0,154 | **-2,012** | -0,298 | **-2,883** |
| Lag 36 | -0,832 | -1,163 | -0,157 | -1,206 | -0,861 | **-2,128** | -0,291 | -0,535 | 0,072 | -1,122 | -1,351 | -0,979 |
| Adj-R2 | 0,236 | | 0,307 | | 0,270 | | 0,324 | | 0,307 | | 0,220 | |
| RMSE | 0,092 | | 0,066 | | 0,076 | | 0,019 | | 0,008 | | 0,054 | |

Table 17 presents summarized results of Fama and MacBeth (1973) regressions for the successful candidate risk factors in the developing equity markets sample. Evaluated factor candidate betas include MKT (excess market return), SMB (size factor), HML (value factor), RMW (operating profitability factor (UMD (momentum factor), UI (unanticipated inflation), LIQ (aggregate liquidity), VOL (aggregate volatility), OIL (return of brent crude oil prices) and TW (trade weight US dollar exchange rates). Three lags of the portfolio returns are also included where Lag 1 is the one-month lag of the test portfolios, Lag 12 uses up to 12 months lags while Lag 36 uses 36 lags of the test portfolio returns. Model 1 document the results of the second pass FM regression without correcting for Errors in variable (EIV) problem Model 2 presents second pass FM regression with corrections to the EIV problem. There are three sample periods, where the first sample period utilizes the data from January 1996 to December 2009, the second subsample period utilizes data from January 2010 to February 2020. The third sample period is the baseline model which covers the whole sample period from January 1996 to February 2020. Standard errors and $t$-statistics are calculated using the Newey and West (1987) adjustment with six lags. $t-$statistics above the 5% (1%) critical level are in bold and italics.

### 5.4.2 Fama-McBeth Regression Output

Table 17 provides estimated average risk prices on the 18-equal weight (EW) 24 value weight (VW), factor-beta sorted portfolios on market factor, and six firm characteristics. There is a considerable difference in the price of risk estimated with EIV and EIV corrections. For instance, before the GFC, there are only three factors priced on the non-EIV corrected portfolios. Market factor (MKT), momentum factor (UMD), and aggregate market volatility factor (VOL) both produce significant risk premiums judged by the lambda ($\lambda_i$) coefficients which are statistically distinguishable from zero. For the EIV corrected portfolios, the period between 1996 to 2009 also yields three significant risk factors but fail to price prior innovations in the test portfolios as revealed by insignificant coefficients of Lag1 to 36. When the full period of the study is considered, again discrepancies arise between non-EIV corrected portfolios and EIV corrected portfolios. For non-EIV corrected portfolios, 7 of the 10 factor candidates produce significant risk premium, while EIV corrected portfolios only yield 5 significant risk factors. Another point of departure is on the lagged returns, EIV corrected portfolios price the first 12 months of memory into the returns, while non-EIV portfolios price between 12 and 36 months of past returns. The two sets of portfolios however fail to price one month lag of returns memory.

The UMD factor is consistently and statistically significant across the sample periods for both EIV corrected and non EIV corrected portfolios. RMW and HML factors are also priced in both the EIV and non-EIV corrected portfolios, but only when the entire sample period is considered. Further examination of the results provided in Table 17 indicates that the size factor does not provide reliable relations with returns of the analysed portfolios. However, SMB is not a big surprise for this study due to its weak statistical significance in the Table. Some earlier empirical indications suggest that the factor provide statistically tractable explanations for the

risk behaviour in developing (frontier) equity markets (Asness et al., 2013; Cakici et al., 2013; Zaremba et al., 2018)

Interpreting the results in Table 17 using the established platforms in asset pricing would require the analysis to begin by discussing significant factors constructed on firm characteristics variables and market factors together. If this norm prevails, then, we can authoritatively submit that only three factors including the market factor are priced in the developing equity markets for the entire sample period of the study. Value and Momentum factors seem to be the exception as the two factors both produce positive risk premiums and are statistically significant at the 1% level for both the EIV and non-EIV corrected portfolios. Excess market return factor (MKT) is typically evaluated alongside firm fundamental variables because it is comprised of all the firms included in a particular stock market and is theoretically postulated to capture all the variation in the market. In the results provided here, the average slope coefficients of market beta are statistically distinguishable from zero and significant at 5% level with $t$ −stat>2.00 for EIV and non-EIV corrected portfolios when the entire sample period is evaluated. The results, therefore, imply that market factor is not only related to the covariance matrix of returns but also commands a reasonable risk premium in the developing equity markets. The factor, albeit presenting a negative premium in the second subsample period, is a risk that cannot be diversified away through any prudent portfolio management.

These results, albeit modest, partly reflect evidence produced by numerous empirical attempts[30] in frontier (developing) equity markets which generally place profitability and momentum factors and to a large extent value factor ahead of other firm fundamental variables in

[30] See for example, Jahan-Parvar and Mohammadi (2013) test three variants of CAPM (market factor) and find evidence supporting market factor as a significant driver of risk in Tehran Stock Exchange. Others such as Zaremba and Maydybura (2019) document strong value and momentum anomalies in frontier equity markets. De Groot et al. (2012) on their part establish that value and momentum factors in frontier emerging markets are statistically and economically significant.

describing risk returns relationships. Equally, there is moderate but sporadic evidence for liquidity and volatility factors in these sets of markets. However, while most of these studies evaluate performance of the factors on nested models like FF three-factor models and alpha tests, our study does not follow their conventions. We evaluate each factor individually based on statistical and economic significance before including them in the asset pricing equation.

Valuable contribution of this study to the asset pricing fraternity, especially to the developing equity markets is the ability to expand the latitude of factors considered as pervasive risk drivers without discrimination based on firm fundamental or macroeconomic orientation. Consequently, this allowed room to assemble a large group of factors in asset pricing. The evaluation criteria and interpretation of the average beta coefficients on the macroeconomic factors is conducted the same way as the firm characteristic factors. Average beta coefficients associated with the macroeconomic variables reveal that the aggregate market volatility factor (VOL) attracts the highest negative risk premium and investors significantly price it at 1% level. In comparison to the other variables after correcting for EIV problem in the baseline model, the relative risk of high volatility in the developing equity markets is captured by the negative risk factor loading of -2.129% per month. Thus, investors in these markets would naturally demand significant compensation for taking up on the risk posed by extremely volatile markets. On the other hand, probably conforming to recent empirical findings such as that of Stereńczak et al. (2020), we find no evidence for liquidity premium in developing equity markets. The finding here is even more interesting since the liquidity variable used in this investigation is market-wide liquidity as opposed to stock level liquidity which studies often find difficult to capture in less developed equity markets.

Another interesting finding explicated by Table 17 is about the inflation factor. Generally, inflation has been a notable barrier to asset management in less developed markets, see for example Farooq and Ahmed (2018) who conclude that higher inflation in less developed

markets weaken the ability of fund managers to make meaningful investment decisions. In this study as reported in Table 17, unanticipated inflation defined as the difference between realized inflation and the expected inflation is only modestly priced in the period preceding the global financial crisis and fails to surmount significant risk premium when the full period of the study is relied on. This output is true for both EIV corrected and non EIV corrected portfolios.

Another central objective advanced in this study, although subtly, is the financial integration of the markets involved in the analysis. The inclusion of global macroeconomic variables was specifically targeted at evaluating whether there are commonalities among these markets, and further if such commonalities are driven by the innovations in the global macroeconomic environment. Evidence in Table 17 indicate that the two global macroeconomic factors do not just relate to the total volatility of returns in these countries, but also attract reasonable risk premium. This is however, only realised post-GFC, but not for the entire period of the study. Innovations on the Brent crude oil prices and the US trade-weighted exchange rate became important for investors in the developing equity markets post the global financial crisis.

*Comparison to emerging and developed equity markets*

As already explained, the study also runs similar analyses for some emerging and developed equity markets for robustness checks. Results are reported in Table 18. We begin the discussion of results in Table 18 by focusing on discernible patterns in the three broad market categories. The test portfolios comprise of 18 equal-weighted (EW), 24 size-weighted (VW), and size-factor beta portfolios pooled from all the firms with complete price data in each of the two asset classes. Even though these sets of markets have enough data points to allow for a more diversified construction, we restrict the construction to the format applied in recent studies. Results reported in Table 18 are summaries obtained from the second-pass regression using EIV corrected and non-EIV corrected portfolios.

**Table 17: Fama and McBeth results for factor in emerging and developed markets**

| | Emerging Markets | | | | Developed markets | | | |
|---|---|---|---|---|---|---|---|---|
| | Model 1: No EIV Correction | | Model 2: EIV Correction | | Model 1: No EIV Correction | | Model 2: EIV Correction | |
| | $\lambda_i$ | $t-$stat | $\lambda_i$ | $t-$stat | $\lambda_i$ | $t-$stat | $\lambda_i$ | $t-$stat |
| Constant | 0,616 | ***4,308*** | 0,870 | ***7,947*** | 0,196 | ***3,784*** | 0,135 | ***5,820*** |
| MKT | 0,327 | ***3,542*** | 0,352 | ***3,859*** | 0,210 | ***3,822*** | 0,169 | ***3,685*** |
| SMB | 0,131 | **2,445** | -0,094 | -1,042 | -0,085 | **-2,475** | -0,677 | ***-3,101*** |
| HML | -0,605 | **-2,455** | 0,027 | ***3,675*** | -0,014 | -1,752 | -0,137 | -1,329 |
| CMA | | | | | 0,008 | 1,767 | -0,186 | **-1,957** |
| RMW | -0,189 | ***-3,542*** | -0,049 | ***-4,057*** | 0,018 | **2,040** | 0,050 | **2,340** |
| DE | | | | | -0,004 | -1,484 | 0,043 | 1,114 |
| IML | -0,183 | -1,670 | -0,043 | -1,052 | | | | |
| UMD | 0,308 | **2,298** | 0,261 | ***3,684*** | 0,818 | **2,677** | 0,068 | **2,925** |
| DEI | 0,375 | 1,450 | 0,213 | 1,121 | | | | |
| UI | -0,031 | **-2,868** | -0,148 | ***-3,053*** | | | | |
| LIQ | -0,014 | **-2,912** | -0,195 | **-2,059** | -0,397 | -1,185 | -0,071 | -1,384 |
| ROL | 0,076 | 1,352 | 0,047 | 1,025 | | | | |
| VOL | -0,080 | ***-4,283*** | -0,070 | **-2,795** | -0,048 | ***-3,208*** | -0,252 | **-4,497** |
| MS | 0,069 | 1,138 | 0,416 | 1,363 | | | | |
| AGR | 0,092 | **2,148** | -0,033 | **-2,666** | | | | |
| CC | | | | | -0,489 | ***-5,118*** | -0,583 | -1,684 |
| GTP | | | | | 0,664 | **2,190** | 0,015 | ***3,906*** |
| GDS | | | | | -0,027 | **-2,121** | 0,018 | 1,807 |
| GI | -0,674 | ***-3,090*** | -0,013 | **-2,173** | 0,154 | 1,741 | 0,031 | 1,362 |
| OIL | 0,540 | 1,185 | 0,027 | 1,829 | 0,062 | 1,850 | 0,010 | ***3,745*** |
| TW$ | -0,193 | **-2,244** | -0,003 | **-2,416** | | | | |
| VX | -0,759 | ***-3,075*** | -0,303 | **-2,881** | -0,072 | ***-11,697*** | -0,373 | -1,666 |
| Lag 1 | -0,552 | **-2,188** | -0,175 | -1,846 | -0,571 | ***-3,963*** | -0,298 | ***-3,216*** |
| Lag 12 | -0,361 | **-2,211** | -0,014 | ***-4,227*** | 0,254 | ***3,712*** | 0,132 | ***3,379*** |
| Lag 36 | -0,169 | ***-3,879*** | -0,063 | **-2,295** | -0,314 | ***-3,901*** | -0,638 | ***-3,026*** |
| Adj-R2 | 0,164 | | 0,259 | | 0,382 | | 0,340 | |
| RMSE | 0,053 | | 0,013 | | 0,039 | | 0,019 | |

Table 18 presents summarized results of Fama and MacBeth (1973) regressions of EW and VW portfolio returns on candidate risk factors. $\lambda_1$ to $\lambda_{20}$ are the coefficients of factors constructed on firm characteristics and macroeconomic variables included in the study. Evaluated factor candidate betas include MKT (excess market return), SMB

(size factor), HML (value factor), RMW (operating profitability factor (UMD (momentum factor), UI (unanticipated inflation), LIQ (aggregate liquidity), VOL (aggregate volatility), OIL (return of Brent crude oil prices) and TW (trade weight US dollar exchange rates). Three lags of the portfolio returns are also included where Lag 1 is the one-month lag of the test portfolios, Lag 12 uses up to 12 months lags while Lag 36 uses 36 lags of the test portfolio returns. Model 1 document the results of the second pass FM regression without correcting for Errors in variable (EIV) problem Model 2 presents second pass FM regression with corrections to the EIV problem. There are three sample periods, where the first sample period utilizes the data from January 1996 to December 2009, the second subsample period utilizes data from January 2010 to February 2020. The third sample period is the baseline model which covers the whole sample period from January 1996 to February 2020. Standard errors and t-statistics are calculated using the Newey and West (1987) adjustment with six lags. t-statistics above the 5% (1%) critical level are in bold and italics Standard errors and $t$ −statistics are calculated using the Newey and West (1987) adjustment with six lags. *, **, and *** respectively indicate that the reported coefficients are statistically significant at 10%, 5%, and 1% levels.

Observations in Table 18 speak to bold, but varying dynamics existing in the three sets of markets in this study. From the onset, results observed in Table 18 if interpreted together with Table 17 suggest that developed markets considerably deviate from the dynamics underlying developing and emerging equity markets innovations. Nonetheless, excess market returns, the market beta (MKT) is statistically significant across the three sets of markets. The table also documents that among the vastly researched characteristics factors, SMB and HML, underpin the glaring differences that exist in risk dynamics in these markets. While SMB is statically significant and priced in the developed market portfolios, the variable proves statistically indistinguishable from zero in both emerging and developing equity markets after correcting for errors is variables problem. The SMB factor also produces negative risk premium for the two sets of markets. HML factor is however priced in all the three categories of markets and attracts positive risk premium for the three categories of markets after correcting for the EIV problem. This outcome is not totally strange and unique to this study, empirical evidence suggests that value premium exists in markets with trading frictions. For instance, Ebrahim, Girma, Shah, and Williams (2014) attribute the presence of value premium in less developed markets to economic fundamentals underlying the markets and investment patterns exhibited by the vast majority of growth firms present in the markets.

Average beta coefficients of UMD factor are also priced in emerging and developing equity markets, but command insignificant risk premium in developed markets. However, factors derived from domestic macroeconomic variables such as UI, LIQ, and VOL produce mixed empirical output for the three sets of the markets under investigation. For instance, the liquidity factor (LIQ) is significantly priced in the emerging market equities but fail to attract reasonable risk premium in both developing and developed equity markets. The volatility factor is however priced in all the three markets with consistent negative risk premiums across the

board. Given that other factors constructed on domestic macroeconomic variables such as Money supply did not qualify for the empirical asset pricing stage for the developing equity markets, their ability or inability to command significant risk premiums in both emerging and developed equity markets are not given much attention as the study was geared towards comparable analysis. Nonetheless, factors such as TW$ and VIX index are found to command significant risk premiums in emerging equity markets.

### 5.4.3 GMM Estimation for the Developing Equity Markets Risk Premiums

The preceding section has so far presented empirical results estimated using Fama and Macbeth (1973) two-pass regression, albeit with modifications from Pukthuanthong et al. (2019). However, potential problems caused by the Errors-in-Variable may plausibly present further implications on the final empirical conclusions. Despite the attempts introduced to solve EIV, it is still reasonable to suspect that distributional drawbacks associated with financial time series data such as heteroskedasticity, autocorrelation, and endogeneity may still be plaguing the ability of the FM model to optimally price the identified risks in the tested markets.

The solution proffered by Pukthuanthong et al. (2019) to construct portfolios using the intersection between size and the resulting beta estimates as test assets instead of individual firm returns has also emerged as inefficient and does not seem to sufficiently cure the problem as demonstrated by Jegadeesh et al. (2019). Consequently, Poshakwale, Chandorkar, and Agarwal (2019) suggest the use of nonparametric techniques in addressing the shortcoming associated with distribution characteristics of the data and the EIV problems inherent in FM procedure. Their procedure follows GMM, while the procedure suggested by Jegadeesh et al. (2019) also favours an instrumental variable (IV) framework closely associated with GMM instrumentation process, but uses individual assets in estimating price of risk.

Given the aforementioned limitations, it is clear that the inadequacies of FM regressions must be fully addressed using a more robust method. GMM is, therefore, proposed, and for a host of

reasons[31], has become a critical component in estimating the price of risk in asset pricing. This is primarily because, in addition to correcting for endogeneity problems, GMM addresses all other problems of non-stationarity in financial data (Cochrane 2005). "… many econometric techniques require assumptions about distribution … the variance formulas in GMM do not include the usual assumptions that variables are i.i.d., normally distributed, homoscedastic, etc. …" (Cochrane, 2009, p. 199).

Despite the notable flexibility and validity of GMM under general statistical conditions, certain conditions precipitate the model. First, GMM relies on moment conditions. One of its desirable flexibilities is the ability to allow the number of moments to exceed the number of parameters being estimated. It however depends on instrumental variable to estimate the parameters of interest and imposes a restriction that the expected values of the moments be zero. Instrumental variables can loosely be referred to as variables with a similar data generating process as the exogenous or regressor variables which must be uncorrelated to the errors process. As Baum, Schaffer, and Stillman (2003) posit, an appropriate set of instruments must be relevant and valid, must also be correlated to the endogenous regressors while maintaining orthogonality conditions with the residual terms. Thus, the instrumental variables must be judiciously chosen. However, the overriding criterion is that the right instruments must be that of the omitted set of variables with explanatory power on the dependent or outcome variable(s). Harvey (1991) conjecture that appropriate set of instrumental variables should be able to approximate the information used by investors to settle on prices of securities. In other words, the variables should be a good predictor of returns. Going by this wisdom, the choice of instrumental variable in this study must therefore be able to address two main components: the global predictors and local predictors. The global factors must be the set that had close relationship with underlying

[31] Cochrane (2009) avers that the variance formulas in GMM do not include the usual assumptions that variables must be i.i.d., normally distributed and homoscedastic.

volatility drivers in both the samples in this study. The local counterparts should then comprise of factors that uniquely drive the utility functions or asset allocation decisions of investors in each market. Consequently, for developing equity markets, the global set of factors used as instrumental variables in the GMM estimation include excess returns of the MSCI index or returns on the global index (GI), lagged values of return on Brent crude oil (one lag), global volatility index proxied by VIX index, global consumer confidence index proxied by US consumer confidence index (CC), and global currency risk proxied by trade weighted US dollar exchange index. The local instruments include changes in expected inflation (DEI), aggregate market volatility (VOL), aggregate liquidity (LIQ), lagged values of market factor (MKT), and lagged values of momentum factor (UDM).

To ascertain validity of the instruments in the GMM estimation, we test for the overidentifying restrictions using $J-$statistic of Hansen (1982). The interpretation of $J-$statistic is thus based on a joint hypothesis of correct model specification and the orthogonality conditions of the resulting error processes. Therefore, we sought to re-evaluate the factor loadings reported in Table 17 and 18 to determine if the factors established to be priced in the developing equity markets maintain their significance.

As has been pointed out, GMM is used to perform a sort of robustness tests to countercheck the validity of the estimated risk premiums associated with firm fundamental factors in developing, emerging, and developed equity markets. Table 19 provide estimated risk premiums of the three sets of markets using GMM. As can be seen, the results in Table 18 are qualitatively similar to the estimated risk premiums in the FM regressions.

**Table 18: GMM regression results for factor candidates risk premiums**

| | 1996 to 2009 | | | | 2010 to 2020 | | | | 1996 to 2020 | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | $\beta_i$ | $t-$stat | $\lambda_i$ | $t-$stat | $\beta_i$ | $t-$stat | $\lambda_i$ | $t-$stat | $\beta_i$ | $t-$stat | $\lambda_i$ | $t-$stat |
| MKT | -0,143 | **-6,873** | -0,735 | ***-5,574*** | 0,186 | ***3,735*** | 2,449 | ***3,346*** | 0,242 | ***4,855*** | 0,584 | ***4,350*** |
| SMB | -0,235 | -1,067 | -0,599 | -1,768 | 0,899 | 1,687 | 0,079 | 1,298 | -0,569 | -1,493 | -0,702 | -1,588 |
| HML | 0,221 | 1,537 | 0,325 | 1,251 | 0,287 | ***3,898*** | 0,423 | **2,526** | 0,373 | ***7,668*** | 0,549 | ***5,184*** |
| RMW | 0,386 | 1,509 | 0,559 | 1,184 | 0,079 | ***3,262*** | -0,727 | ***-3,839*** | -0,802 | -1,240 | -0,945 | -1,941 |
| UMD | 0,276 | 1,872 | 0,033 | 0,475 | 0,259 | **2,434** | -0,043 | **-3,211** | 0,536 | ***3,164*** | 0,856 | ***4,174*** |
| UI | -0,650 | ***-4,134*** | 0,559 | ***3,601*** | 0,845 | **2,374** | 0,727 | ***3,681*** | 1,099 | **1,986** | 0,945 | ***2,086*** |
| LIQ | 0,299 | **2,093** | 0,260 | ***5,767*** | -0,389 | **-2,721** | -0,338 | -1,697 | -0,505 | -1,537 | -0,439 | -1,296 |
| VOL | -0,851 | **-2,392** | -6,006 | **-2,184** | -0,806 | ***-3,110*** | -7,808 | **-2,839** | -33,548 | ***-4,042*** | -1,150 | ***-3,691*** |
| OIL | 0,338 | **1,860** | 0,286 | 1,483 | 0,439 | 1,718 | 0,372 | 1,228 | 0,571 | 1,833 | 0,483 | 1,196 |
| TW$ | 0,754 | 1,134 | 0,650 | 1,588 | -0,980 | ***-5,374*** | -0,845 | ***-4,664*** | -1,274 | **-2,986** | -1,099 | ***-3,064*** |
| Adj- $R^2$ | 0,315 | | 0,299 | | 0,379 | | 0,386 | | 0,400 | | 0,258 | |
| RMSE | 0,099 | | 0,079 | | 0,059 | | 0,123 | | 0,066 | | 0,096 | |
| J-stat | 3,546 | | 4,623 | | 3,569 | | 2,852 | | 3,459 | | 4,986 | |
| P-Value | 0,223 | | 0,185 | | 0,346 | | 0,159 | | 0,229 | | 0,237 | |

This table presents summarized results of GMM regressions of EW and VW portfolio returns on candidate risk factors. $\beta_i$ is the coefficients associated with the factor $i$ constructed either on firm characteristics or macroeconomic variables, while $\lambda_i$ is the coefficient associated with the beta of each factors in the analysis. $\lambda_i$ is the price of risk or the coefficient of the beta. Evaluated factor candidates include MKT (excess market return), SMB (size factor), HML (value factor), RMW (operating profitability factor (UMD (momentum factor), UI (unanticipated inflation), LIQ (aggregate liquidity), VOL (aggregate volatility), OIL (return of Brent crude oil prices) and TW (trade weight US dollar exchange rates). Three lags of the portfolio returns are also included where Lag 1 is the one-month lag of the test portfolios, Lag 12 uses up to 12 months lags while Lag 36 uses 36 lags of the test portfolio returns. Model 1 document the results of the second pass FM regression without correcting for Errors in variable (EIV) problem Model 2 presents second pass FM regression with corrections to the EIV problem. There are three sample periods, where the first sample period utilizes the data from January 1996 to December 2009, the second subsample period utilizes data from January 2010 to February 2020. The third sample period is the baseline model which covers the whole sample period from January 1996 to February 2020. Standard errors and $t-$statistics are calculated using the Newey and West (1987) adjustment with six lags. $t-$statistics above the 5% (1%) critical level are in bold and italics.

Results presented in Table 19 largely confirm the evidence of FM regressions in Table 17, but with a few deviations when the full sample is considered. For starters, the coefficient signs largely remain unchanged. Few important points evident in Table 19, however, need to be highlighted: first, having addressed the econometric problems[32], GMM is known for, the statistical power of the coefficient estimate on value factor, HML, increases from 3.677 to 5.184. Secondly, the ability of the SMB factor to price equity returns in developing equity markets largely remains unchanged with insignificant average beta coefficient. Thirdly, the profitability factor is now only marginally priced in the markets, and all the three domestic factors yield mixed results.

For instance, over and above pricing the market-wide volatility in the returns, GMM establishes that unanticipated inflation (UI) commands significant and reasonable risk premium in the developing equity markets. Results of GMM indicate that investors in these markets are concerned about the changes in general prices, and thus demand significant compensation for bearing such risk in their portfolios. Observing the full sample period in Table 19 indicate that coefficient of UI is statistically distinguishable from zero, suggesting that after correcting for the inefficiencies of the FM model, the factor turns out to not only be a significant driver of risk, but priced in developing equity market returns with a $t$ −statistic of 2.086. The aggregate market volatility factor VOL has however remained steadfast in its ability to influence returns differentials and command risk premium. The factor has proved to be an important component of investors decisions calculus in the tested markets. The negative risk premium of -0.15, is highly statistically significant at 1% level with t-stat of -3.691.

[32] Major econometric problems in financial time series data such as the one in this study may range from as endogeneity, heteroscedasticity, to autocorrelation. These problems, especially endogeneity become less of a concern once a GMM procedure is used to analyse the data.

**Table 19: GMM results for factors in emerging and developed equity markets**

| | Emerging | | | | Developed | | | |
|---|---|---|---|---|---|---|---|---|
| | $\beta_i$ | $t-$stat | $\lambda_i$ | $t-$stat | $\beta_i$ | $t-$stat | $\lambda_i$ | $t-$stat |
| MKT | 0,199 | **2,155** | 0,214 | ***3,672*** | 0,200 | **3,369** | 0,161 | **3,125** |
| SMB | 0,080 | 1,488 | -0,057 | **-1,991** | -0,081 | **-2,355** | -0,645 | **-2,951** |
| HML | -0,368 | **2,493** | 0,017 | ***3,497*** | -0,013 | **-4,522** | 0,131 | **2,217** |
| CMA | | | | | 0,007 | 1,681 | -0,177 | -1,862 |
| RMW | -0,115 | **2,155** | -0,030 | ***-3,860*** | 0,017 | 1,941 | 0,047 | **2,227** |
| DE | | | | | -0,003 | -1,412 | 0,041 | 1,060 |
| IML | -0,111 | -1,016 | -0,026 | -1,827 | | | | |
| UMD | 0,187 | ***3,810*** | 0,159 | ***3,505*** | 0,778 | **2,548** | 0,064 | **2,784** |
| DEI | 0,228 | 1,274 | 0,130 | 1,678 | | | | |
| UI | 0,019 | **2,528** | 0,090 | **2,905** | | | | |
| LIQ | -0,008 | **-2,772** | -0,119 | **-1,996** | -0,378 | -1,128 | -0,068 | -1,317 |
| ROL | 0,046 | **0,822** | 0,029 | 1,198 | | | | |
| VOL | -0,049 | **-2,606** | -0,043 | **-2,660** | -0,046 | ***-3,052*** | -0,240 | ***-4,280*** |
| MS | 0,042 | 0,692 | 0,253 | 1,297 | | | | |
| AGR | 0,056 | 1,307 | -0,020 | -1,585 | | | | |
| CC | | | | | -0,465 | **-2,870** | -0,554 | -1,603 |
| GTP | | | | | 0,632 | **2,084** | 0,014 | **3,717** |
| GDS | | | | | -0,025 | **-2,019** | 0,017 | 1,910 |
| GI | 0,410 | 1,880 | 0,008 | **2,067** | 0,147 | 1,657 | 0,029 | 1,296 |
| OIL | 0,329 | **2,172** | 0,016 | 1,740 | 0,059 | 1,761 | 0,009 | ***3,564*** |
| TW$ | -0,118 | -1,965 | -0,002 | **-2,299** | | | | |
| VX | -0,462 | -1,871 | -0,185 | **-2,742** | -0,068 | **-11,131** | -0,355 | ***-5,857*** |
| Adj-R2 | 0,257 | | 0,313 | | 0,382 | | 0,340 | |
| RMSE | 0,099 | | 0,053 | | 0,099 | | 0,045 | |
| J-stat | 2,444 | | 1,030 | | 1,6175 | | 1,298 | |
| P-Value | 0,363 | | 0,486 | | 0,140 | | 0,191 | |

This table presents summarized results of GMM regressions of EW and VW portfolio returns on candidate risk factors in emerging and developed equity markets. $\beta_i$ is the coefficients associated with the factor $i$ constructed either on firm characteristics or macroeconomic variables, while $\lambda_i$ is the coefficient associated with the beta of each factors in the analysis. $\lambda_i$ is the price of risk or the coefficient of the beta. Evaluated factor candidates include MKT (excess market return), SMB (size factor), HML (value factor), CMA (investment factor) RMW (operating profitability factor), DE (Debt-to-equity ratio factor), IML (firm level liquidity factor), (UMD (momentum factor), DEI (changes in expected inflation factor), UI (unanticipated inflation), LIQ (aggregate liquidity), ROL (Rule of Law), VOL (aggregate volatility), MS (money supply), AGR (agricultural commodity index), CC (US consumer confidence index), GTP(global term premium), GDS (global default spread), GI (global market index proxied by MSCI index), OIL (return of Brent crude oil prices) and TW$ (trade weight US dollar exchange rates. Columns 2 to 5 document the results of emerging equity markets, while columns 6 to 9 presents the developed markets results. The sample period covers the whole the period from January 1996 to February 2020. Standard errors and $t-$statistics are calculated using the Newey and West (1987) adjustment with six lags. $t-$statistics above the 5% (1%) critical level are in bold and italics

It is imperative to interrogate results presented in Table 19 based on model stability and fitness. GMM estimation is generally plagued with either overfitting or underfitting the instruments (Baum et al., 2003). $J-$statistics and associated $p-$values as presented in Table 19 are used to test the hypothesis of the overidentification of the instruments. $J-$stat of 4.986 with $p-$ values of 0.237 for the entire sample period fail to reject the null hypothesis of correct model specification. Results presented in last two columns in Table 19 are consistent, and thus the null hypothesis prevails.

Results in Table 20 do not deviate considerably from the counterparts of FM results reported in Table 19. Table 19 also report that AGR cease to be significant in determining returns variations in the emerging markets. The picture is also consistent with the results on developing equity markets where factors found significantly priced using FM regressions largely maintain their statistical powers even when a more robust GMM regression is employed. Despite the confirmation of the results in Table (s) 16, 17, and 18, GMM results in Table 19 present smaller $t-$statistic across the significant factors in both emerging and developed markets. $J-$statistic and their associated $p-$values indicate that the models were optimally identified, fitted, and the right instruments were used to determine the moment conditions of the model.

### 5.4.4 Estimating price of risk using Arbitrage Pricing Theory (APT) framework

We continue to underscore the valuable contribution of this study to asset pricing knowledge in developing equity markets. This is demonstrated partly by not only grounding the analysis and the description of the underlying risk drivers on a particular predetermined theoretical or empirical approach but by providing a wider latitude for all the competing approaches in asset pricing to describe the structure of risk in developing equity markets. Thus, having followed a framework largely predicated on the CAPM and its variants thus far, attention is now directed towards evaluating risk pricing in developing equity markets using pervasive state variables approach. This approach has historically been anchored on Arbitrage Pricing Theory (APT).

The model postulates existence of more than one pervasive state variable influencing returns variation in the markets, largely because market observed events do not always result in a uniform movement for all the major shocks in the economy. For instance, a shock in the real economy may result in positive gains or returns to some firms while others experiencing downward effects. The recent COVID-19 pandemic is a clear example. Anecdotal evidence already suggests that firms whose services complimented the work from home dynamics experienced huge positive spikes in their values, while majority of the sectors experienced declining value. Similarly, due to investor expectations, pharmaceutical companies involved in the search for vaccination have performed fairly-well through the pandemic as investors anticipated the breakthrough would result into higher returns.

Nonetheless, the identity of the relevant state variables that span APT pricing framework has been a matter of conjecture. Studies associate some of the discovered variables with weak correlation with asset prices hence producing almost insignificant results in empirical asset pricing tests (see, for example, Azeez and Yonezawa, 2006). Kleibergen (2009) on their part assert that when factors are only weakly correlated with cross-section of asset returns, their betas tend to be small, and inferences on risk premia using the linear based procedures such as Fama-McBeth procedure may potentially be spurious. This, therefore, has forced researchers to instead use mimicking portfolios of the macroeconomic factors in evaluating their influence on risk-return trade-offs in capital markets. Theoretically leaning explanation to this phenomenon include Breeden (1979) and Huberman, Kandel, and Stambaugh (1987) who argue for mimicking portfolios in successful implementation of APT.

In terms of implementation, we use equal weight portfolio of industry returns with complete observations on 16 macroeconomic factors identified earlier in this study. Construction of industry portfolios has often presented a challenge for asset pricing in markets with trading

frictions. To counter the shortcoming, we implement a procedure introduced by Berger et al. (2011) to construct equal weight industry portfolio returns even for countries without complete industry data. Data are obtained from Thompson Reuters DataStream and Bloomberg databases. Analysis conducted in this section is done using Fama and McBeth (1973) two-pass regression procedure, and the errors and $t-$stats are calculated using the Newey and West (1987) adjustment with six lags.

Table 21 reports each country's results of standard two-pass regression of Fama and MacBeth (1973) using portfolio of industry returns. The estimated prices of risk shown by the average beta coefficients of each of the macro factor are evaluated on the size of the accompanying $t-$statistic. In line with the principle established earlier in this study, a variable is only considered significant or priced when the associated $t-$stat of the risk price ($\lambda$) is at least 2.0, and significantly different from zero at 5% level of significance. The sign of the average beta coefficient indicates the relationship between returns and the macro variables.

A total of 16 macroeconomic variables comprising of 7 domestic and 9 international factors are considered for the description of risk-return relations in 20 developing equity markets. Results in Table 20 suggest that unanticipated inflation (UI), aggregate liquidity (LIQ), and market volatility factors attract significant risk premium in majority of the markets in the study. Precisely, risk price of UI is found statistically distinguishable from zero in Argentina, Bangladesh, Croatia, Kazakhstan, Kenya, Kuwait, Nigeria, Oman, Pakistan, Romania, Slovenia, Sri Lanka, and Vietnam. Albeit being significantly priced in the 13 of the 20 developing equity markets, the factor is attracting negative risk premium, except in Croatia and Argentina. There is economic justification for a negative relationship between stock returns and inflation surprises: thus, the sign of the UI conforms to the a priori which stipulates those

changes in unexpected inflation can influence the perception of investors regarding future cash flows eventually affecting the current prices.

Consequently, investors would require substantial compensation for taking on inflation risk (Virk, 2012). It is also possible to expect a significant relationship between stock returns and unexpected inflation because unexpected inflation accommodates new information regarding future rates of inflation which investors need to discount their future cash flows in real earnings. Azeez and Yonezawa (2006) argue that if the information is negative for the stock market, and if the newly released Consumer Price Index (CPI) data contain new information about inflation, then unexpected inflation should be associated with a decrease in stock prices at the time of the announcement because it influences nominal cash flows, hence the negative risk premium reported for the 11 developing equity markets.

Aggregate liquidity (LIQ) or market wide liquidity factor is significantly priced, but the sign of the coefficient is negative, indicative of negative risk premiums for most of the markets it is priced in the sample. Negative risk premium displayed by the average coefficient of aggregate liquidity beta possibly postulate that low liquidity would prompt investors to demand higher future expected returns thus depressing the current stock prices evaluably leading losses that would ultimately yield negative risk premium. Surprisingly, two of the governance-related variables namely rule of law (ROL) and regulatory quality (REQ) seems to not command any significant risk premiums in majority of the countries in the study, except Croatia, Jordan, Lithuania, and Mauritius. The associated $t-$statistics of the two variables falls short of the established cut-off point indicating their inability to systematically influence returns variations in all the three markets in the sample.

The results here are in contrast to the empirical evidence presented by Sherif and Chen (2019) who establish that governance indicators such as accountability, government effectiveness, and

control of corruption significantly influence international momentum profits. However, any conclusion regarding momentum patterns needs to be taken with a grain of salt, because of the inconsistencies surrounding momentum profits. Furthermore, this study has used equal weighted industry portfolios. Average beta coefficient of stock market volatility VOL is established to be statistically different from zero in all of the markets. Volatility as has been observed in this study, commands substantial risk premium mainly due to its pervasiveness and magnitude in the developing equity markets.

One of the characteristics established earlier in this study is that the markets in the primary sample are heavily characterised by persistent volatility, especially at the macro level. Volatility results from market sentiment, news regarding fundamental drivers in the economy and general state of the economy. The characteristics established so far indicate that the markets under consideration here present quite volatile macroeconomic environment, partly due to unfavourable political environments and due to weak institutional capacities (Thampanya, Wu, Nasir, and Liu, 2020). This should, however, not be surprising as the factor is directly constructed from overall prices of all markets comprised in the industry portfolios.

Money supply, MS, is yields modestly significant risk premiums in five markets. This is more so in oil producing countries with the average beta coefficients significantly different from zero at the 5% level except for Tunisia ($t$ =1.69). Positive relationship between money supply and stock returns gets theoretical support from Quantity Theory of Money (QTM). Friedman and Schwartz (1963) hold that money supply influences economic activities resulting in increase in cash flows which leads to higher demand for financial stocks as an outlet for excess liquidity. Our findings here partly contrasts those of Bahloul et al. (2017), who report mixed evidence on changes in money supply in a panel of developed, emerging, and frontier markets. In our results, money supply only attracts significant risk premium in 5 of the 20 markets.

**Table 20: Fama-MacBeth Local factors Results for Developing Markets Equity based on APT**

| | Local Factors | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | DEI | | UI | | LIQ | | REQ | | ROL | | VOL | | MS | |
| | $\lambda_{DEI}$ | $t-$stat | $\lambda_{UI}$ | $t-$stat | $\lambda_{LIQ}$ | $t-$stat | $\lambda_{REQ}$ | $t-$stat | $\lambda_{ROL}$ | $t-$stat | $\lambda_{VOL}$ | $t-$stat | $\lambda_{MS}$ | $t-$stat |
| Argentina | 5.18 | 1.41 | 3.25*** | **4.08** | -9.33** | **-2.89** | 4.40** | **2.68** | 0.41 | 1.01 | -17.55** | **-2.94** | 1.13 | 1.59 |
| Bahrain | 3.74 | 1.07 | -1.50 | -1.43 | -5.27** | **-2.55** | 1.03 | 1.01 | 1.74* | **1.78** | -1.56** | **-2.63** | 7.32*** | **5.11** |
| Bangladesh | 0.23 | 1.35 | -1.24** | **-2.94** | -5.25** | **-2.64** | 4.26 | 1.62 | 0.27 | 1.44 | -1.28** | **-2.17** | 0.28 | 1.57 |
| Croatia | 5.79* | **1.72** | 2.54 | **2.46** | -0.29 | -1.92 | 3.05 | 1.37 | 1.08 | 1.62 | -2.05*** | **-18.24** | 0.30 | 1.12 |
| Jordan | -1.09** | **-2.10** | -0.32 | -1.51 | -1.55*** | **-3.16** | 4.75 | 1.06 | 0.02 | 1.30 | -0.25*** | **-4.50** | 1.48*** | **4.32** |
| Kazakhstan | 0.46 | 1.48 | -1.84** | **-2.48** | -0.22*** | **-4.40** | 2.60 | 1.54 | 0.20 | 1.12 | -1.04** | **-2.54** | 1.11 | 1.58 |
| Kenya | 0.54 | 1.36 | -0.23** | **-2.29** | -1.31*** | **-183.64** | -0.61 | -1.43 | -2.30 | -1.35 | -2.20** | **-2.31** | 4.19 | 1.11 |
| Kuwait | 0.41 | -1.24 | -0.12*** | **-13.50** | -2.08*** | **-57.87** | 0.55 | 1.11 | 0.26 | 1.57 | -2.31** | **-2.94** | 0.27 | 1.59 |
| Lithuania | -1.03** | **-2.62** | -2.08 | -1.02 | -7.12*** | **-3.11** | -4.17 | -1.57 | -1.22 | -1.63 | -2.26** | **-2.60** | -5.31 | -1.47 |
| Mauritius | 1.15** | **2.60** | -0.06 | -1.53 | 7.08*** | **-3.35** | 0.34 | 1.48 | 0.11*** | **7.03** | -0.13** | **-2.29** | 11.14*** | **16.38** |
| Morocco | 0.11 | -1.37 | -1.19 | -1.04 | -2.27*** | **-4.59** | 2.35 | 1.16 | 0.43 | 1.25 | -6.51** | **-2.12** | 1.76 | 1.51 |
| Nigeria | 0.17 | -1.55 | -8.26*** | **-5.55** | -3.35*** | **-3.83** | 1.44 | 0.44 | 1.53 | 0.48 | _1.32** | **-2.44** | 5.07 | 1.19 |
| Oman | -22.08 | -1.13 | -4.28** | **-2.06** | -1.47** | **-2.06** | -6.67 | -1.53 | -1.47 | -1.35 | -7.40** | **-2.24** | 3.46** | **2.59** |
| Pakistan | -1.08 | -1.63 | -1.25** | **-2.58** | -1.42*** | **-4.30** | -1.58 | -1.21 | -1.75 | -1.53 | -0.49*** | **-46.09** | 5.06 | 1.70 |
| Romania | -0.16 | -1.59 | -0.20*** | **-42.09** | -0.44*** | **-3.54** | 0.88 | 1.86 | 1.32 | 1.16 | -0.75*** | **-4.27** | 11.13 | 1.36 |
| Serbia | -0.75 | -1.27 | -2.32 | -1.60 | -0.13*** | **-17.78** | -0.46 | -1.58 | 0.03 | 1.38 | -0.16*** | **-5.02** | 0.18 | 1.48 |
| Slovenia | -0.25 | -1.64 | -0.65*** | **-4.11** | -0.35 | -1.01 | -0.05 | -0.26 | 0.75 | 1.61 | -0.45 | **-1.71** | 2.14 | 1.61 |
| Sri Lanka | -2.14 | -1.02 | -0.30*** | **-85.62** | -1.81** | **-2.25** | -0.64 | -1.24 | -0.47 | -1.13 | -0.31** | **-2.11** | 0.14 | 1.57 |
| Tunisia | -0.32 | -1.40 | -0.27 | -1.14 | -0.21** | **-2.47** | 0.16 | 1.63 | -0.11 | -0.06 | -0.05*** | **-73.45** | 0.30** | **1.99** |
| Vietnam | -0.20 | -1.58 | -7.57** | **-2.65** | -0.06** | **-2.73** | 1.71 | 1.31 | 0.18 | 1.29 | -0.85* | **-1.94** | 0.12 | 1.35 |

Table 21 presents summarized results of Fama and MacBeth (1973) regressions of industry portfolio returns on macroeconomic risk factors. The abbreviations DEI stands for changes in expected inflation, UI is unanticipated inflation, LIQ is aggregate liquidity, REQ is regulatory quality, ROL is rule of law, VOL is aggregate volatility, while MS is changes in M2 money supply. $\lambda$ is the price of risk for domestic macroeconomic factors in each of the developing equity markets included in the study. Standard errors and $t$-statistics are calculated using the Newey and West (1987) adjustment with six lags. *, **, and *** respectively indicate that the reported coefficients are statistically significant at 10%, 5%, and 1% levels

Turning to global macro factors, results provided in Table 21 indicate that most of the developing equity markets are exposed to innovations in the global macroeconomic environment. Agricultural commodity Index, US consumer confidence, Global stock market index, oil prices, US dollar trade weighted exchange rates and US volatility index command significant risk premiums in a good number of the countries included in this study. This finding underscores the significance of global risk factors in the stock market investment in the developing equity markets. Having discovered at factor identification phase using canonical correlations that many of the factors in this category are significantly related to the total volatility of returns in these markets, the results in Table 21 appear to suggest that these markets may be integrated with the global markets.

The average beta coefficient associated with agricultural commodity index AGR ($\lambda_{AGR}$) is statistically significant in 14 developing equity markets. Results in Table 21 indicate that average beta coefficient of agricultural commodity index in developed equity markets is statistically indistinguishable from zero, hence not priced and unable to command reasonable risk premium in Bangladesh, Kuwait, Lithuania, Morocco, Serbia, and Tunisia. It should be noted that most of the countries in the developing and emerging equity markets in this study are major producers of agricultural commodities, and hence commodities contribute significantly to the trading and economic earnings. Countries such as Sri Lanka, Kenya, and Argentina, are significant producers of soybeans, beef rice, coffee, tea, and a range of horticultural products which are important earners to their overall economic coffers. It is, therefore, explicable that these country's broad returns generating processes are highly driven by the variations in the agricultural commodity index.

**Table 21: Fama-MacBeth Global factors Results for Developing Markets Equity under APT**

| | Global Macroeconomic Factors | | | | | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | AGR | | UCC | | GTP | | GDS | | MTL | | GI | | OIL | | TW$ | | VIX | |
| | $\lambda_{AGR}$ | $t-$stat | $\lambda_{UCC}$ | $t-$stat | $\lambda_{GTP}$ | $t-$stat | $\lambda_{GDS}$ | $t-$stat | $\lambda_{MTL}$ | $t-$stat | $\lambda_{GI}$ | $t-$stat | $\lambda_{OIL}$ | $t-$stat | $\lambda_{TW\$}$ | $t-$stat | $\lambda_{VIX}$ | $t-$stat |
| Argentina | 0.18 | **2.53** | -0.86 | 1.28 | 0.19 | 1.28 | 0.01 | -0.71 | 0.09 | 1.06 | -0.16 | **-4.14** | -0.24 | **-2.88** | -0.31 | **-2.82** | -0.39 | **-3.90** |
| Bahrain | -0.25 | **-2.07** | -0.61 | **-3.50** | -0.38 | 1.68 | -0.14 | 1.06 | -0.03 | -1.87 | -0.67 | **-3.09** | 0.43 | **7.35** | -0.19 | -0.89 | -0.20 | **-7.64** |
| Bangladesh | 0.30 | 1.41 | -0.31 | -1.29 | -0.32 | -1.82 | 0.33 | 1.78 | -0.34 | -1.52 | 0.35 | **-2.30** | 0.36 | **2.72** | 0.37 | 0.32 | -0.38 | -1.33 |
| Croatia | 0.18 | **2.86** | -0.55 | **-2.58** | -0.30 | -0.12 | 0.05 | 1.44 | 0.18 | -2.75 | 0.55 | **-3.46** | 0.30 | **2.23** | 0.05 | **2.14** | -0.18 | **-2.93** |
| Jordan | -0.19 | **-3.26** | -0.17 | **-2.07** | 0.41 | 1.32 | 0.64 | 1.11 | 0.29 | **1.99** | 0.10 | **-2.14** | 0.33 | **4.61** | 0.36 | **2.99** | -0.79 | **-4.18** |
| Kazakhstan | -0.49 | **-3.66** | 0.19 | -1.60 | -0.24 | -1.62 | 0.62 | 1.83 | -0.03 | -1.18 | 0.38 | **-2.67** | 0.76 | **2.85** | 0.14 | **3.66** | -0.51 | **-4.06** |
| Kenya | 0.26 | **4.10** | 0.75 | -1.14 | -0.44 | -1.92 | -0.13 | -1.50 | -0.82 | -1.42 | -0.51 | **-6.71** | -0.20 | **-2.25** | -0.89 | **-2.36** | -0.58 | **-2.09** |
| Kuwait | -0.11 | -1.30 | -0.82 | **-7.68** | -0.54 | -1.22 | 0.25 | 1.16 | 0.40 | -1.65 | 0.68 | **-4.14** | 0.39 | **4.67** | 0.10 | **2.47** | -0.31 | **-2.22** |
| Lithuania | -0.40 | -1.85 | -0.44 | -1.07 | -0.49 | -1.27 | -0.53 | -1.88 | -0.58 | -1.89 | -0.62 | -1.83 | -0.67 | -1.31 | -0.71 | -0.42 | -0.76 | -1.46 |
| Mauritius | -0.17 | **-7.35** | -0.19 | -1.60 | -0.20 | -0.52 | 0.22 | 1.55 | 0.24 | -0.03 | 0.25 | **-2.41** | -0.27 | **-2.55** | 0.28 | **2.18** | -0.30 | **-9.20** |
| Morocco | -0.35 | -1.44 | -0.84 | -1.09 | -0.39 | -1.82 | 0.20 | 0.17 | -0.08 | -1.31 | 0.16 | **-9.28** | 0.24 | **2.88** | 0.32 | 1.79 | -0.40 | 1.88 |
| Nigeria | 0.40 | **2.84** | -0.39 | -1.83 | 0.08 | 1.02 | 0.17 | 0.89 | -0.26 | -0.50 | 0.35 | -1.61 | 0.44 | **17.25** | -0.53 | -1.94 | -0.63 | 1.04 |
| Oman | -0.46 | **-2.24** | -0.45 | **-2.17** | -0.05 | -1.17 | -0.95 | -1.60 | -0.44 | **-2.79** | -0.29 | **-2.35** | 0.44 | **2.72** | -0.43 | -1.68 | -0.43 | **-5.20** |
| Pakistan | -0.42 | **-2.23** | -0.59 | **-2.70** | -0.28 | -1.52 | -0.92 | -1.27 | -0.09 | **-1.98** | -0.26 | **-89.25** | 0.43 | **29.78** | -0.59 | **-2.49** | -0.76 | **-34.67** |
| Romania | -0.07 | **-4.08** | -0.51 | **-3.24** | -0.21 | -1.81 | -0.39 | -1.99 | -0.83 | -1.21 | -0.27 | -1.48 | 0.71 | **2.48** | -0.15 | -1.28 | -0.59 | -1.74 |
| Serbia | 0.32 | 1.43 | -0.89 | -1.68 | -0.06 | -1.11 | -0.03 | -1.66 | -0.60 | -1.45 | -0.17 | **-5.27** | -0.74 | -1.60 | -0.31 | -1.58 | -0.88 | -1.18 |
| Slovenia | 0.56 | **2.78** | -0.26 | -1.32 | -0.30 | -1.06 | -0.66 | -0.27 | -0.37 | -1.69 | -0.07 | -1.31 | -0.77 | -1.21 | -0.47 | -1.89 | -0.17 | -1.62 |
| Sri Lanka | 0.80 | **3.12** | -0.24 | **-2.06** | 0.47 | 1.36 | -0.30 | -1.04 | -0.13 | **-2.93** | -0.40 | **-2.22** | -0.80 | **-2.80** | -0.63 | **-51.89** | -0.46 | **-5.07** |
| Tunisia | -0.89 | -1.47 | -0.34 | -1.19 | -0.18 | -1.61 | -0.73 | -1.71 | -0.68 | -0.96 | -0.63 | **-2.62** | 0.57 | **5.14** | 0.52 | **2.34** | -0.47 | **-2.33** |
| Vietnam | 0.26 | **5.17** | -0.12 | **-2.73** | -0.19 | **-2.01** | -0.26 | -1.38 | -0.33 | -1.35 | -0.40 | **-2.09** | -0.47 | -1.46 | -0.54 | **-2.06** | -0.21 | **-5.13** |

Table 22 presents summarized results of Fama and MacBeth (1973) regressions of industry portfolio returns on macroeconomic risk factors. The abbreviations AGR stands for agricultural commodity Index, UCC is United States consumer confidence index, GTP is global term premium, GDS is global default spread, MTL is metal index, GI is global stock market return index, OIL is the changes in brent crude oil, TW$ is US trade-weighted exchange rates index, while VIX is the US volatility index. $\lambda$ is the price of risk for global macroeconomic factors in each of the developing equity markets included in the study. Standard errors and $t$-statistics are calculated using the Newey and West (1987) adjustment with six lags. *, **, and *** respectively indicate that the reported coefficients are statistically significant at 10%, 5%, and 1% level

### 5.5 Further tests for the priced risk factors

So far, we have employed a battery of empirical procedures to investigate priced risk factors in developing equity markets. The reason behind the variety of the empirical exercises employed is to avoid proliferation of factors spanning the risk structure in developing equity markets, and to also ensure model parsimony. We take pride in both theoretical and empirical implications of the approaches adopted in uncovering the underlying risk drivers in developing equity markets. However, in conformity to the myriads of prominent asset pricing works, a further approach needs to be undertaken to firmly ascertain the findings already documented in this study. To execute this, a procedure theoretically advanced by Belloni, Chernozhukov, and Hansen (2014) and later empirically implemented by Feng et al. (2020) in an exercise to identify important asset pricing factors is adopted. This approach, the Double Selection LASSO (DS-LASSO) is thus aimed at checking the robustness of the priced factors already established in the preceding sections.

The Double Selection Lasso strategy discussed in Chapter 3 and intended for this section is implemented through two-pass regression of Fama and MacBeth (1973). Reported results, therefore, only include the final model showing the statistical summaries and point estimates of selected risk factors. Our strategy is based on Feng et al. (2020) criteria, who divide asset pricing factors into two groups. In chapter 3, we named these groups as $g_t$ and $h_t$ and where the former are considered relevant risk factors, highly related to the underlying drivers of return generating mechanisms, and possibly priced as risk factors in the returns, while the latter are factors mildly related to underlying drivers of returns volatility. Unlike Feng et al. (2020), we do not have hundreds of factors from which to select the ones that significantly explain asset prices. However, given that DS-LASSO is flexible to low dimensional space, our analysis is conducted with the constraints in the few factors in the sample.

This study has assembled a total of 26 factors suspected to describe risk-return relationships in developing equity markets. The preceding analyses in this chapter have established that some of the factors are priced in the returns on equities of the tested markets. Implementing DS-LASSO requires two sets of factors, $(g_t)$ which is the focal variable and $(h_t)$, the control variables (factors). If we strictly take the route of Feng et al. (2020) we will have to produce a large group of $(h_t)$ factors to be the control variables, and possibly use the factors we have already established as priced to be the $(g_t)$ focal variables. Unfortunately, we do not have this luxury in our data since there can only be up to 26 factors to implement the model.

Given the foregoing, starting from a clean slate requires that a set of $(g_t)$ be established. Therefore, we must estimate the price of risk for a variable (s) to be considered focal in DS-LASSO first step of analysis. To ensure uniformity, and to further enable comparability in the analysis, we test for significantly priced common factor(s), that is, factors priced in all the three markets to include as a $(g_t)$ candidate. Using all the 26 variables as the potential $(g_t)$ candidates for the three asset classes, FM two step regression (reported in Appendix A) establishes that MKT and HML are consistently priced in all the three markets. Average beta coefficients of the two factors are statistically significant and consistent across the three markets. Therefore, the two factors are employed as the $(g_t)$ focal factors as required by the model.

Having established the common risk drivers in all the three markets, we then treat all the remaining factors as control factors $(h_t)$. That is, the factors suspected to have modest explanatory power on returns but may be linearly related to the focal factor MKT and HML. In ordinary tests, we would easily call off the analysis and pronounce MKT and HML as the only priced factors across the markets. However, as noted earlier in the motivation of DS-LASSO, omitting the other variables is construed as omitted variable bias because the control

factor may add new information to the HML factor in describing risk-return structure in these markets.

Table 23 reports results of DS-LASSO analysis alongside other models to ensure that the selected factors are void of any uncertainty in describing stock returns in developing equity markets. The first column indicates the factors selected through the benchmark model DS-LASSO. Column two reports the price of risk, $\lambda$, accompanied by the associated $t-$stats. Price of risk and the associated $t-$stats of the selected variables are estimated suing Fama-MacBeth two-step regression procedure. Column three reports the single LASSO (SS) selection together with the price of risk $\lambda$ and associated $t-$stats, respectively estimated using FM two-pass regressions. Columns four and five, respectively, report the results of stepwise regression and OLS regressions together with their beta coefficients $\beta$ and associated $t-$stats.

Using DS-LASSO selection criteria, only six factors comprising of market factor, value factor, momentum factor, unanticipated inflation, market wide volatility, changes in crude oil prices, and trade weighted US exchange rates are selected in the developing equity markets. In emerging markets, the procedure selects seven risk factors including MKT, HML, SMB, RMW, UMD UI, VOL and GI. In developed markets, up to 9 factors are selected. Note that developing equity markets only produce one firm characteristic factor, UMD alongside market factor. While emerging markets produce three additional firm fundamental factors including SMB, RMW and UMD. Of note is that UMD is selected in both developing and emerging equity markets, while developed markets do not select the factor. Again, developed market is the only asset class where investment factor is selected. SMB and RMW are conspicuously missing in the developing equity markets, while selected for the other two categories of the markets. Without determining whether these factors are priced in the securities of these markets or not, there is noticeable difference in the reported results, where apart from HML, the only

other factor associated with considerable market frictions, UMD is selected to move returns in both developing and emerging markets, but not in developed markets.

Column two reports estimated risk prices using FM regressions. Accordingly, only three of the additional (selected using DS-LASSO) factors add new explanatory power to MKT and HML in describing returns in developing equity markets. Beta coefficients of HML and MKT, are statistically different from zeros at 1% respectively, while UMD, VOL and TW$ are at 5% level suggesting that the five factors attract significant risk premiums in the developing equity markets. The level of significance depicted by HML, and MKT factors are not surprising since the initial analysis already established that two factors are priced across the markets.

Column three reports results of standard LASSO dimensional reduction technique together with FM two-step regression analysis. An eyeball observation reveals that only market factor is identified and hence found as priced using the single selection LASSO across the three markets. Note that SS-LASSO has been subjected to the full sample set of the available risk factors in all the three markets in the study. Column three results appear as restrictive since only one factor is consistently identified and priced across the markets. Standard LASSO, as Feng et al. (2020) reports, does not work well with finite samples and can mistakenly exclude factors with small in-sample exposure to the variable of interest.

In column four, stepwise least squares regression model, a standard model for factor selection is employed to offer comparative analysis of the factors selected in the study. In conducting stepwise regression, HML is included as the focal variable of interest, then the rest of the factors identified through the benchmark model introduced as search regressors. Results in the first panel of Table 23 indicate that all the factors are identified and are found significant at 1% level. Comparatively, the $t$ −stat values of stepwise regression are much larger, suggesting that the model is prone to accepting factors that may otherwise be redundant. However, there is

evidence in the literature questioning robustness of stepwise regression in factor selection (Hegyi and Garamszegi, 2011; Tso and Yau, 2007; Wang, Wright, Brownlee, and Buswell, 2016; Whittingham, Stephens, Bradbury, and Freckleton, 2006). Opponents of stepwise regression argue that the model is prone to type $I$ error, where there is high likelihood of the model selecting factors as significant even when in reality they are not. In Table 23, it can be observed that all the factors selected using DS-LASSO are all significant with increased size of the $t$ −statistic.

Turning to the last column of Table 23, OLS regression is used in the estimation. Just like the stepwise regression, majority of the selected factors are found statistically significant using OLS. There is already plethora of evidence eviscerating parameter estimates of OLS as efficient estimators.

**Table 22: Factor Selection and Two-pass regression: additional tests**

| | Model 1:DS-LASSO | | Model 2: SS-LASSO | | Model 3: STEPLS | | Model 4: OLS | |
|---|---|---|---|---|---|---|---|---|
| *Developing Equity Markets* | | | | | | | | |
| S. Factors | $\lambda_S$ | $t-$stat | $\lambda_S$ | $t-$stat | $\beta_S$ | $t-$stat | $\beta_S$ | $t-$stat |
| MKT | 0,67 | **3,72*** ** | 0,44 | 1,03 | 1,27 | **6,43*** ** | 0,72 | **4,73*** ** |
| HML | 0,83 | **4,10*** ** | 0,50 | **2,44** ** | 0,69 | **4,44*** ** | 0,63 | **2,82** ** |
| UMD | 0,57 | **2,96** ** | 0,30 | 1,30 | 0,18 | **3,42*** ** | 0,86 | **2,96*** ** |
| UI | -0,84 | -1,958 | -0,43 | -1,62 | -0,15 | **-2,28** ** | -0,72 | **-3,37*** ** |
| VOL | -0,50 | **-2,15** ** | -0,57 | 1,05 | -0,95 | **-3,10*** ** | -0,40 | **-2,51** |
| OIL | -1,37 | -1,73 | -1,18 | 0,80 | 0,88 | **3,46*** ** | 0,91 | **2,60** ** |
| TW$ | -0,10 | **-2,52** ** | -0,41 | 1,15 | -0,16 | **-2,62** ** | -0,58 | -1,78 |
| *Emerging Equity Markets* | | | | | | | | |
| MKT | 0,91 | **4,11*** ** | 0,78 | 1,48 | 1,19 | **5,70*** ** | 1,89 | **4,50*** ** |
| HML | 0,89 | **3,13*** ** | 0,09 | **2,11** ** | 0,38 | 1,39 | 0,33 | **2,90** ** |
| SMB | 0,12 | **1,99** ** | 0,62 | 0,75 | -0,07 | 1,41 | -0,58 | **-2,00** ** |
| RMW | -0,41 | **-2,47** ** | -0,26 | -0,64 | -1,70 | **-6,93*** ** | -0,67 | **-7,37*** ** |
| UMD | 0,93 | **2,18** ** | 0,29 | 1,51 | 0,83 | **5,13*** ** | -0,23 | -1,82 |
| UI | -3,70 | -0,63 | -0,23 | -1,04 | -8,41 | -1,77 | -0,53 | **-2,81** ** |
| VOL | -0,10 | -1,15 | 0,22 | 0,84 | -2,53 | **-2,49** ** | -0,15 | **-2,71** ** |
| GI | -1,32 | **-2,07** ** | -0,05 | 0,14 | -1,27 | -1,71 | -0,63 | **-2,86** ** |
| *Developed Equity Markets* | | | | | | | | |
| MKT | -0,19 | **-2,51** ** | -0,45 | -1,60 | -0,12 | -1,08 | -0,07 | **-2,17** ** |
| HML | 0,49 | **7,36*** ** | 0,68 | **5,94*** ** | 0,51 | **3,83*** ** | 0,59 | **6,09*** ** |
| SMB | 0,08 | **2,21** ** | 0,09 | 0,70 | 0,21 | **2,29** ** | 0,07 | **2,77** ** |
| CMA | -0,13 | -1,47 | -0,56 | -0,96 | -0,47 | -1,93 | -1,19 | -1,48 |
| RMW | -0,07 | -0,76 | -0,75 | -1,08 | -0,62 | -1,29 | 0,81 | **3,85*** ** |
| IML | 0,07 | 0,70 | 0,20 | 0,83 | 0,16 | 1,76 | 0,12 | **2,36** ** |
| UI | -0,16 | **-2.41** ** | -0,59 | -0,88 | -0,49 | **-3,71*** ** | -1,21 | **4,70*** ** |
| UCC | -0,15 | **-2.07** ** | -0,37 | -0,92 | -0,55 | -1,23 | -0,43 | **2,86** ** |
| GI | 0,44 | 1,26 | 0,34 | 1,20 | 0,38 | **3,39** | 0,37 | 1,43 |
| VIX | -0,22 | -0,84 | -0,66 | -1,03 | -0,03 | -1,15 | -0,47 | **-42,83*** ** |

Table 23 reports results of robustness checks using Double selection LASSO as the benchmark model. $\lambda_s$ is the estimated price of risk and accompanied by the corresponding t-statistic. The Factors reported in column 1 are the successful factors selected using Double Selection LASSO criteria in each category of the market. MKT and HML factors were used as the pre-selected ($g_t$) factors for DS-LASSO for all the three markets. In column two, the benchmark model DS-LASSO is estimated with two-pass regression of Fama and MacBeth (1973). Column three reports the results of single LASSO selection, also estimated with FM two-pass regression while column four and five respectively reports stepwise regression and ordinary least squares tests for the selected factors. Beta coefficients of factors in columns four and five are not subjected to two pass regressions of FM. $t-$stat values in bold indicate significant coefficients of the factor's betas. Standard errors and $t$-statistics are calculated using the Newey and West (1987) adjustment with six lags. *, **, and *** respectively indicate that the reported coefficients are statistically significant at 10%, 5%, and 1% level.

### 5.5 Remarks

The study has found important empirical results on asset pricing in developing equity markets. First, the study has established that only a few fundamental drivers influence returns in the sampled developing equity markets. At country level, factor identification strategy employed discovered that only a few principal components were significantly related to the covariance matrix of returns. Canonical correlations analysis largely confirmed the results as factors such as excess market returns, book-to-equity and aggregate volatility significantly influenced returns variations in most of the individual markets in the sample.

The empirical evaluation of the identified factors further established that excess market returns (MKT), book-to-market (value) factor (HML), profitability factor (RMW), momentum factor (UMD), unanticipated inflation factor (UI), aggregate volatility (VOL), and trade weighted US dollar index (TW$) were significantly priced in the returns of developing equity markets. Although FM regression did not price UI and TW$, the associated $t-$statistic of their coefficients were closer to the threshold value of 2. For instance, UI and TW$ respectively produced $t-$stat 1.952 and 1.929, which are significant at the 10% level. The GMM analysis, used for robustness checks, confirmed that MKT, HML, UMD and VOL were significantly priced, but further found that both UI and TW$ were not only significant drivers of risk variations, but also priced in the returns of developing equity markets.

Further, DS-LASSO was used as a robustness check on the entire system starting from the factor identification to testing the identified factors. The results are not further from the conclusions of GMM, as MKT, HML, UMD and TW$ are found to be significantly priced in the developing equity market returns. The results also indicated that UI is marginally priced with a t-stat of 1.958.

### 5.6 Out-of-sample tests

Having established important risk drivers and factors priced in the sampled markets, it is empirically logical to test the same factors in an out-of-sample setting. That is, can the results hold when a different sample is interrogated? Given the primary focus of this study, a framework is required for developing equity markets, hence the out-of-sample test undertaken in this section draws from two developing equity markets: Bulgaria and Oman. The choice of this sample just as before, is purely guided by the availability of data.

The risk drivers identified by the two main factor identification procedures of canonical correlation and double-selection LASSO for developing equity markets are investigated. Data paucity was identified as a significant constraint in the combined sample, and still continue to bedevil the out-of-sample data especially in constructing some of the previously identified risk factors. For instance, size variable was not readily available for the entire period in the Bulgarian market.

The sample include all listed companies with available stock price data in the two markets. The data period is from 01:2010 to 04:2021, resulting in 136 months of total observation. Bulgaria has 400 firms with complete data over the period, while Oman has 144 firms with data. Just like the combined sample, financial firms are not excluded from the sample, as their omission would results in very few firms with reliable data to construct the risk factors. Returns are computed in US dollars, to take the perspective of global investor. Factor construction follows a similar procedure used for the main sample in the preceding analyses. Table 24 presents results of GMM estimation, favoured for the out-of-sample markets because of its robustness to many of the previously encountered problems such as endogeneity, heteroskedasticity and many other challenges associated with parametric estimation procedures.

**Table 23: Out of sample tests using GMM**

| | Bulgaria | | | | Oman | | | |
|---|---|---|---|---|---|---|---|---|
| | $\beta_i$ | $t-$stat | $\lambda_i$ | $t-$stat | $\beta_i$ | $t-$stat | $\lambda_i$ | $t-$stat |
| MKT | 0,69 | ***4,32*** | 0,15 | ***3,16*** | 0,03 | ***3,76*** | 0,59 | ***3,31*** |
| SMB | -0,43 | -1,02 | -0,08 | -1,69 | -0,03 | -1,76 | -0,23 | -1,36 |
| HML | 0,16 | **2,00** | -0,98 | **-2,22** | -0,15 | -1,38 | -0,40 | **-2,89** |
| RMW | -0,10 | **-2,43** | -0,04 | **-2,46** | -0,24 | **-2,19** | -0,30 | -1,66 |
| UMD | 0,36 | ***4,86*** | 0,11 | ***3,15*** | 0,33 | **2,80** | 0,28 | ***3,24*** |
| UI | -0,88 | -1,45 | -0,23 | -1,53 | 0,51 | ***3,38*** | -0,36 | **-2,05** |
| LIQ | -0,15 | -1,74 | -0,30 | -1,22 | 0,60 | 1,57 | -0,55 | -1,90 |
| VOL | -0,41 | **-2,04** | -0,36 | **-2,90** | 0,69 | ***5,76*** | -0,34 | ***-3,85*** |
| OIL | 0,93 | 1.68 | 0,49 | ***3,28*** | 0,87 | **8,14** | 0,72 | ***5,66*** |
| TW$ | 0,96 | **2,41** | 0,50 | 1,81 | 0,96 | **2,33** | 0,31 | **2,56** |
| Adj- $R^2$ | 0,26 | | 0,28 | | 0,34 | | 0,26 | |
| RMSE | 0,03 | | 0,01 | | 0,08 | | 0,06 | |
| J-stat | 2,20 | | 3,32 | | 1,23 | | 1,96 | |
| P-Value | 0,55 | | 0,79 | | 0,50 | | 0,24 | |

This Table presents the out of sample test using GMM. $\beta_i$ are the coefficients associated with the factor $i$ constructed either on firm characteristics or macroeconomic variables, while $\lambda_i$ is the coefficient associated with the beta of each factors in the analysis. $\lambda_i$ is the price of risk or the coefficient of the beta. Evaluated factor candidates include MKT (excess market return), SMB (size factor), HML (value factor), RMW (operating profitability factor (UMD momentum factor), UI (unanticipated inflation), LIQ (aggregate liquidity), VOL (aggregate volatility), OIL (return of Brent crude oil prices) and TW$ (trade weight US dollar exchange rates). Standard errors and $t-$statistics are calculated using the Newey and West (1987) adjustment with six lags. $t-$statistics above the 5% (1%) critical level are in bold and italics.

The results, reported in Table 24, largely mirror the already established findings in the combined sample of developing equity markets in this study. Evidently, the market factor MKT performs relatively well in the two out-of-sample markets, with Bulgaria providing up to 0.15% monthly risk premium returns over the 136 months period while Oman produces about 0.59% monthly returns. The evidence in Table 24 also reaffirm that the SMB factor is not significantly priced in the developing equity market returns. The factor produces statistically insignificant risk premiums for the two out-of-sample markets in Table 24. Bulgaria positively prices the HML factor while Oman market has negative risk premiums associated with the HML factor. Momentum factor UDM is positively priced in the two out-of-sample markets. The two markets also factor in aggregate market liquidity in their risk calculus, but significantly price overall market volatility in their returns. This is also generally in tandem with the findings from the combined sample.

On the whole, there are three firm level risk factors priced in the Bulgarian market including HML, RMW and UDM. In addition, the significance of market factor MKT suggests that the debate sounding the market beta may not be fully addressed in this study. The differences established in the ability of RMW to significantly drive returns differentials in Bulgaria but fail to attract significant risk premiums in Oman further throws additional conundrum on what factors can exactly be pronounced as the real drivers of returns in developing equity markets. The results established here however do not significantly deviate from the myriads of studies that have found mixed results for the frontier market equities. For instance, Alhashel (2021) find mixed results for GCC markets. The author established that size premium exists in all the markets investigated while B/M factor only produces significant returns premium in some of the countries in the analysis. Similarly, Zaremba (2015) finds that value and momentum premiums exist in Central European countries, but size premium is lacking. However, the size effect has been observed to be on the decline over the years. In many studies, the micro caps have been outperforming the big cap firms, hence Zaremba (2015) suggests that a new approach must be devised, especially in markets dominated with small cap firms if the traditional factor pricing models have to be used to evaluate equity returns in such markets.

# CHAPTER 6

# CONCLUSION AND RECOMMENDATIONS

## 6.1 Introduction

Asset pricing has attracted innumerable attention of many stakeholders in capital markets. However, there is still a considerable lack of consensus regarding the full list and identity of risk factors and even the ability of the already studied risk factors to optimally price risk in stock markets across the globe. This problem as highlighted in this study is more pronounced in the developing equity markets due to the unpredictability of the underlying risk fundamentals. The study also highlighted that many of the markets comprising developing equity markets are characterised by considerable market frictions that do not align well with the established asset pricing fundamentals which further complicates the pricing of risk in such markets using the existing frameworks. Other confounding factors include sizeable downside risk, stale prices, acute illiquidity, and unstable macroeconomic fundamentals. This study has been built around these highlighted constraints and the aim was to chart course for pricing equity risk in the developing equity markets while taking the saliant constraints into account.

Given the path asset pricing work has travelled, this study took notice of the overwhelming contributions towards a universally accepted asset pricing framework for all the markets of the world. Many of the guiding principles that shaped this work were taken directly from endeavours such as those of Fama and French (1992, 1993, 1996, 2012, 2015 and 2017), as well as the ones of Ross (1976), Chen, et al. (1986) and many more influencing works. Despite the controversies that still lingers, these works have yielded varying but fundamental discoveries, especially pertaining to the identity of risk drivers and their exact influence on securities prices. In this study, the major task was to first identify asset pricing risk factors, and then test the selected factors to ascertain whether they are priced in the developing equity

market returns. The rationale behind these two objectives emanates from the thesis that, despite numerous innovations and research, dynamics in the developing countries are still at odds with the original theoretical underpinnings of asset pricing theories. Given this disparity, this study largely depended on the ability of the available risk factors to span the risk space in the developing equity markets, thereby allowing the study to completely depend on the ability of the available data to tell the full story despite the associated data problems in developing equity markets.

## 6.2 Pricing risk in developing equity markets

To address the highlighted objectives, the study implemented the theoretical fundamentals laid down in both APT and CAPM frameworks to estimate the price of risk in the developing equity markets. The first objective which is strategically advanced to identify important risk drivers in developing equity markets is a weighty subject in asset pricing discourse, regardless of the markets in which the studies are undertaken. For instance, Feng et al. (2020) and Feng, Giglio, and Xiu (2020) submit that factor identification remains the cornerstone of asset pricing. The second objective, the empirical evaluation of the identified risk factors is also crucial, not only for finance researchers but for all the stakeholders including investors and policy bureaucrats. The second objective attempts to settle the longstanding debate on asset pricing, especially in markets still considered for portfolio risk diversification by many investors across the globe. Just to know the identity of the factors may be necessary, but to conclusively determine whether the known factors significantly command risk premium, are priced, and can be traded is sufficient and a considerable contribution to the body knowledge asset pricing.

Given the centrality of the first objective – to identify important drivers of returns in developing equity markets –, this study employed a battery of empirical procedures. Starting with a large pool of both macroeconomic and firm characteristics variables to choose from, 10 significant drivers of returns volatility in developing equity markets were identified.

Considering the challenge faced by researchers in the process of factor identification, one needs to tread carefully to avoid the existing confusion. For example, in an attempt to impose discipline to the curse of dimensionality ubiquitous in asset pricing, Fama and French (2018) advance a right-hand-side spanning regression procedure to choose from a gamut of nested and non-nested asset pricing models using maximum squared Sharpe ratio. Harvey et al. (2016) on the other hand employs, a frequentist approach to select from a large pool of factors, warning that discovery of any new factors from the zoo that already exists must impose a restrictive summary statistical hurdle, for instance, $t$ −statistic equal to 3 or above.

While these suggestions are aimed at improving the efficacy of the factors that pass empirical asset pricing methods, the perspective presented by Pukthuanthong et al. (2019) and Kelly et al. (2019) finely resonate with the overarching objective of this study. Pukthuanthong et al. (2019) for instance, proposes a nuanced sturdy protocol to select from amongst many potential candidate risk factors. Their methodology is specifically favoured by this study for its ability to innovatively handle both left-hand-side and right-hand-side variables selection separately.

Using the same protocol at country level, we found that only a few dominant drivers generally drive returns in majority of the countries in the sample. The necessary condition which employed standard PCA discovered for instance that the first PC in Argentina, Bahrain, Croatia, Tunisia, and Vietnam control over 30% of total returns variations, and the first 3 PCs account for over 80% of total volatility in the markets. The finding has significant implications on asset pricing, given the debate surrounding the many discovered asset pricing factors. If only a few variables or risk drivers suffice to describe entire market returns, then the principle of parsimony in asset pricing is validly advanced. On the other hand, the revelation that total volatility in Argentina, Bahrain, Croatia, Tunisia, and Vietnam is dominated by one perversive

factor which controls over 50% of total variance implies the presence of one domineering factor, in which the asset pricing discourse has always associated with the market factor.

Expectedly, similar trend was discovered in a combined sample of all the developing equity markets employed in the study. The 10-risk factor identified in a combined sample of developing equity markets include market factor MKT, size factor SMB, value factor HML, profitability factor RMW, momentum factor UDM, unanticipated inflation factor UI, aggretgate liquidity factor LIQ, aggregate volatility factor VOL, brent crude oil factor OIL, and US dollar trade-weighted exchange rates TW$. In the spirit of comparative analysis, and to also validate the findings of the study, a group of emerging and developed equity markets were also investigated alongside 20 developing equity market asset classes.

As already indicated, the empirical evaluation of the identified risk factors and the estimation of the price of risk was conducted using Fama and MacBeth (1973) two-step and GMM regression procedures for all the three asset classes in the study. For developing equity markets, market factor (MKT), value factor (HML), profitability factor (RMW), momentum factor (UMD), unanticipated inflation (UI), market-wide volatility (VOL), and trade-weighted US dollar exchange rates (TW$) were found to be priced in the returns. The size factor was, however, consistently insignificant in the returns of developing equity markets. The use of GMM regression analysis was due to its robustness to stochastic distribution challenges which may have influenced the summary parameter estimates in the FM regressions. However, GMM results largely confirmed that the factors significant in the FM regressions retained their statistical significance.

The final empirical procedure was strategically focussed on checking the statistical robustness of the protocol used in the initial analysis which selected and tested factors. This was done using the procedure of Feng et al. (2020) who employ Double Selection LASSO to identify

and test priced risk factors from a large pool of all the factors introduced into the asset pricing calculus over the years. To complement their methodology, we introduced a standard variable selection model, stepwise regression whose performance was not as spectacular given its document empirical challenges. Through DS-LASSO, 7 factors including MKT, HML, UMD, UI, VOL, OIL, and TW$ were selected from the available pool of 26 candidate risk factors in developing equity markets. However, of the 7 five factors including excess market returns, HML, momentum, aggregate volatility, and US dollar trade weighted exchange rate index were found to be significantly priced in the developing equity market returns. For emerging markets, DS-LASSO analysis selected 8 factors and found that factors such as HML, MKT, SMB, RMW, UMD, and GI were significantly priced in their returns. While 10 factors were selected for the developed markets, where HML, MKT, SMB, CMA, UI, and UCC were significantly priced in the developed equity market returns. Comparatively, these results suggest the existence of significant disparities between the three sets of markets investigated. For instance, the size factor (SMB) does not attract significant risk premium in developing equity markets but is significantly priced in both emerging and developed equity markets. The results also evidently show that investment factor, CMA is not related to the underlying risk fundamentals in both developing and emerging equity markets but are related to returns volatility and priced in the developed markets.

## 6.3 Policy Implications

Many underlying policy implications can be drawn from this study. First, given the increased investor attention to developing equity markets, it is plausible that a favourable policy environment can accelerate capital market development and investment in these countries. On the contrary, a few pieces of literature highlight that the policy positions of many countries are at the core of derailing investment, developments, and research. For instance, judicious implementation of asset pricing studies has consistently been met with substantial obstacles

across the world in the presence of certain policy impediments instituted by authorities to safeguard their interests. Some of the impediments include foreign exchange controls, and capital controls that authorities use to shield their financial sectors and by extension capital markets from adverse external pressures.

In the wake of the Asian financial crises, for example, a number of countries took tougher policy steps to remedy the total collapse of their financial systems. Countries such as Thailand, South Korea, and Indonesia opted for IMF prescriptions perceived to be relatively liberal, while others such as Malaysia instituted tough capital controls to avoid capital flights and protect their vulnerable currencies from further depreciation. While examining the impact of Malaysia's capital control measures on exchange rates and stock prices, Ramasamy and Yeung (2002) established that the policy was ineffective and did not effectively yield the desired impact to the financial sector and economy at large. Likewise, as a pragmatic policy counter to the devastating impact of the Global Financial Crisis, many authorities in the West such as the European Central Bank, Bank of England, US Federal Reserve Bank, and Japanese monetary authority instituted brazen monetary policy tools to boost their economy, and by extension investment in their capital markets. Miyakoshi, Shimada, and Li (2017) investigated the impact of Quantitative Easing (QE) imposed by Bank of England, European Central Bank, and Bank of Japan on stock prices in emerging Asian stock markets and established that the policy increased stock price inflation in the emerging and developing stock markets.

In this study, some of the global macroeconomic variables investigated did not provide a significant influence on risk-return relations despite a plethora of evidence suggesting their impact on stock returns in other countries. For instance, excess returns of the global equity index proxied by excess returns of MSCI did not seem to significantly influence returns in the developing equity markets in the study. Pasricha, Falagiarda, Bijsterbosch, and Aizenman

(2018) highlight that possible explanations can be ascribed to lack of capital markets integration, while Chinn and Ito (2006) cite poor or lack of capital markets integration is a symptom of capital control measures common in many developing countries. Similarly, despite the reported impact of global industrial production index proxied by OECD industrial production index on return generating process in many countries across the world, see for example Gjerde and Saettem (1999) and Atanasov (2018), the variable could not be included in this study due to lack of or poor relationship (results excluded) with returns in developing equity markets.

Accounting variables such as capitalization, book-to-market ratio, total assets, accruals, debt-to-asset ratio, total revenue, sales volume, among others have been the leading variables investigated in asset pricing research across the globe. Fama and French (1992, 1996) proclaim that accounting information proxy for common pervasive risk drivers in stock markets. Therefore, accounting, and financial reporting are crucial to the information provided by these variables. However, developing equity markets are still plagued by poor or lack of prudent and harmonised accounting practices largely blamed on poor enforcement of corporate governance policies (Pillai and Al-Malkawi, 2018). Consequently, variables hinged on quality accounting information such as earnings predictability did not provide any relationship with the underlying drivers of returns in developing equity markets in this study.

Lack of well-established debt (bond) markets in developing economies also feature prominently as a besetting drawback to investment and development of their capital markets. In such countries, capital is largely raised through the inadequate banking system which limits the amount of capital available for both private and public sectors. As argued by Ojah and Kodongo (2015) this may have undesirable consequences on financing projects that require large capital outlay like railway development, building of large physical infrastructures which

literature generally tie to the overall development of the economy. In developed and emerging markets, debt variables such as corporate bonds and government bonds form a significant component of capital market investment and are important drivers of returns in their stock markets. Unfortunately, developing equity markets do not have well-functioning debt markets rendering the variables irrelevant in their risk-return equation. Thus, these countries should institute deliberate policy measures to ensure growth of debt markets.

## 6.4 Recommendations for further research

Considering the amount of work already undertaken in asset pricing, the ongoing discoveries, and the existing controversies, it is highly unlikely that the present study can conclusively address the ever-elusive equity premium puzzle. However, specifically to developing equity markets, we take pride in providing a roadmap to addressing some of the glaring gaps. This is achieved by diligently undertaking an elaborate empirical exercise comprised of the largest pool of countries in developing equity markets. The study has also assembled a long list of factors considered important for altering the wealth position of investors in the developing equity markets. Empirical test of the priced factors has also revealed factors important for risk diversification in the emerging markets. However, the study falls short in presenting a nested equity pricing model in the developing equity markets.

Moving forward, the unattended components of this study would be a worthwhile undertaking by future research. Apart from not presenting a nested asset pricing model, the study has also not been able to use industry variables to construct asset pricing factors despite recent literature increasingly including industry characteristics as possible asset pricing factors.

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## APPENDICES

### Appendix A: Fama-MacBeth Regression for all the 26 factors

| | Developing | | Emerging | | Developed | |
|---|---|---|---|---|---|---|
| Factors | Gama | t-stat | Gama | t-stat | Gama | t-stat |
| MKT | 0,61 | **4,68** | 0,33 | **3,54** | 0,17 | **3,68** |
| SMB | -0,54 | -1,16 | 0,13 | 1,84 | -0,68 | **-3,10** |
| HML | 0,66 | **3,94** | -0,61 | **2,45** | 0,14 | **2,33** |
| CMA | 0,30 | 0,86 | -0,98 | -1,73 | -0,19 | **-2,96** |
| RMW | 0,93 | 1,96 | -0,19 | **3,54** | 0,05 | **2,34** |
| DE | 0,83 | 1,87 | -0,16 | 1,53 | 0,04 | 1,11 |
| IML | -0,98 | -1,18 | -0,13 | -1,67 | 0,05 | 1,97 |
| UMD | 0,79 | **2,97** | -0,31 | **-2,30** | 0,07 | **2,93** |
| PMU | -0,17 | -1,74 | -0,28 | -1,69 | 0,65 | **2,74** |
| PMN | 0,39 | 1,40 | -0,39 | -1,60 | 0,11 | 1,80 |
| DEI | 1,30 | 0,99 | 0,38 | 1,45 | 0,19 | 1,75 |
| UI | -0,63 | 1,97 | -0,31 | -0,87 | 0,14 | 1,92 |
| LIQ | -0,62 | **-2,16** | -0,71 | **-2,91** | -0,68 | -1,38 |
| REQ | -1,19 | -1,82 | -0,28 | -1,14 | -0,88 | -1,37 |
| ROL | -0,32 | 0,64 | 0,08 | 1,35 | -0,62 | -1,89 |
| VOL | -0,83 | **-6,03** | -0,08 | **-4,28** | -0,25 | **-4,50** |
| MS | -1,62 | 1,54 | 0,07 | 1,14 | -0,19 | **-1,70** |
| AGR | 0,49 | 1,80 | 0,09 | **2,15** | -0,24 | -1,26 |
| CC | -0,15 | -0,33 | -0,03 | -0,38 | -0,58 | -1,68 |
| GTP | -0,42 | -0,48 | 0,26 | -1,42 | 0,01 | 3,91 |
| GDS | -0,69 | -0,63 | 0,19 | -1,55 | 0,02 | 2,01 |
| MTL | -0,95 | -0,79 | 0,36 | -1,28 | 0,42 | 1,81 |
| GI | -0,95 | 1,47 | -0,67 | **-3,09** | 0,03 | 1,36 |
| OIL | 0,57 | 1,69 | 0,54 | **2,19** | 0,01 | 2,74 |
| TW$ | -0,40 | -1,53 | -0,19 | **-2,24** | -0,37 | -1,39 |
| VX | -0,36 | -1,46 | -0,76 | **-3,07** | -1,09 | -1,67 |
| Adj-R2 | 0,256 | | 0,299 | | 0,172 | |
| RMSE | 0,348 | | 0,119 | | 0,198 | |

This table reports Fama-MacBeth Regression results for all the 26 factors candidate risk factors for monthly (1996 M01 to 2020 M02) firm characteristic variables sorted on $(2 \times 3)$ and macroeconomic variables, domestic and international. Significance tests marked in bold indicate 5% level of significance. MKT is the individual country market returns of all the firms with complete data less one-month US Treasury bill rate. At the end of each year (June), stocks are allocated into two size groups using $70^{th}$ and $30^{th}$ percentiles to represent big (B) and small (S) stocks, respectively. Stocks are further assigned independently to three book-to-market equity (BM), investment (Inv), operating profitability (OP), Liquidity (LIQ), Momentum (UMD), predictability (PRD), and persistence (PRT) groups, using 30th and 70th percentiles of individual country stocks. HML is the portfolios formed from the intersection of the Size and BM sorts $(2 \times 2)$, investment, profitability, leverage, liquidity, momentum, predictability, and persistence factors, CMA, RMW, ROA, IML, UMD, PMU, and PMN, use six value weight portfolios from the intersection of the Size and the subsequent characteristic sorts. SMB, size factor (Small Minus Big) is the average return on the eighteen small stock portfolios minus the average return on the eighteen big stock portfolios. Domestic macroeconomic variables are

DEI (changes in expected inflation), UI (unanticipated inflation), LIQ (aggregate liquidity), REQ (regulatory quality) ROL (rule of law), VOL (returns volatility), and MS (broad money supply, M2). Global macroeconomic variables are AGRIC (agricultural commodity index), CC (US Consumer confidence), Metal (return on the composite metal index), GI (excess return of Morgen Stanley Capital International Index), OIL (return on crude oil prices), TW$ (US dollar broad trade-weighted exchange Index), VIX (US volatility index).