Modern Finance

Article

Pricing the common stocks in emerging markets: The role of economic policy uncertainty

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Abstract: We examine the role of news-based policy uncertainty measures in capturing the cross-section of average stock returns in emerging markets. After controlling for the five established risk factors of Fama and French (FF), we find that policy uncertainty factors are redundant in capturing the average returns of portfolios constructed by considering well-known firm characteristics (size, book-to-market ratio, profitability, and investment). The pricing performance of the five factors model, both statistically and economically, does not improve with the addition of policy uncertainty factors. We argue that the news-based factors' information content is contained in FF risk factors. Our results are robust to additional test statistics and various policy uncertainty factors.

Keywords: asset pricing; emerging markets; factor models; policy uncertainty; cross-section of returns; equity anomalies; the five-factor model

JEL: G11; G12; G15

1. Introduction

Although there is substantial evidence showing a tendency to favour domestic assets in investment portfolios, the overall trend of global financial integration has promoted the sharing of risks and the ability for foreign investors to diversify their holdings. [1] International investors seek to diversify their investment portfolios by incorporating assets from emerging markets. Consequently, knowing the market dynamics, risk sources, and the cross-section of returns in these markets is crucial for investors (Kim & Lee, 2020).

Fama and French (2015, 2017) claim their model can explain the variations in the cross-section of returns, and their factor-mimicking portfolios capture the systematic risks associated with unexpected shifts in the underlying macroeconomic fundamentals. However, there is no consensus on their model's performance in emerging stock markets.[2] The variation in the model's performance can be attributed to the contrasting dynamics of these markets compared to the developed markets (Rajeb et al., 2015). Emerging markets are often characterised by higher political uncertainty and geopolitical risk (Zaremba et al., 2022). Additionally, increasing integration among emerging markets makes them vulnerable to global geopolitical risks through policy uncertainty channels (Cheng & Chiu, 2018; Salisu et al., 2022). Although there is ample evidence that unanticipated deviations from economic policies regarding fiscal, monetary, regulatory, and trade affairs have a documented impact on asset prices internationally (Baker et al., 2016; Azimli, 2022; Hu et al., 2018; Kundu & Paul, 2022; Xu et al., 2021; Das & Kumar,

Citation: Arkol, O, & Azimli, A. (2024). Pricing the common stocks in emerging markets: The role of economic policy uncertainty. *Modern Finance*, *2*(1), 31-50.

Accepting Editor: Adam Zaremba

Received: 20 November 2023
Accepted: 29 January 2024
Published: 31 January 2024

[1] See Karolyi and Stulz (2003) and Fidora et al. (2007).
[2] See Azimli (2020), Lin (2017), Zaremba and Czapkiewicz (2017), Singh and Tripathi (2020), Mosoeu and Kodongo (2022) for instance.

2018; Hoque & Zaidi, 2020; Sekandary & Bask, 2023, and others), the evidence whether global economic policy uncertainty (GEPU) is an undiversifiable risk that commands a risk premium in emerging markets is scarce.

Against these backdrops, we aim to test whether global economic policy uncertainty (GEPU) plays a role in explaining the cross-section of returns in emerging markets after accounting for the Fama and French's five risk factors. If GEPU is actually a distinct systematic factor that commands a risk independently from the five risk factors of Fama and French (FF), then incorporating GEPU into their model should enhance its asset pricing ability. To achieve this objective, we utilize test portfolios constructed by considering established firm fundamentals such as size, profitability, investment, and book-to-market ratio (B/M) from 24 emerging countries' equity markets. We treat the stock return data as pooled for several reasons. Zaremba et al. (2019) show that the extent of integration increased globally in the equity markets over the past 30 years. Liquidity and other market frictions are in the nature of emerging markets which hardens the financial integration process (Castiglionesi et al., 2017). Nevertheless, in addition to Cheng and Chiu's (2018) findings, Mishra et al. (2022) provide an analysis of the 24 emerging equity markets[3], acknowledging the presence of some regional disparities in equity market integration. However, despite the disparities, they conclude the markets are integrated. In addition, their research highlights the predominant roles of China and India, designated as 'power hubs' within this emerging market network. This distinction emphasizes the considerable influence and interconnectedness of these two countries in the broader context of emerging market networks. Since our portfolio formation utilizes market capitalizations as a weighting mechanism and these countries have the highest market capitalizations in the sample, our test portfolios, and factor mimicking portfolios are skewed towards stocks of these countries. Hence, it may be contended that there is a high level of interconnectedness among the markets we utilize. Indeed, Kim and Lee (2020) showed that institutional investors tend to rebalance their portfolios with emerging market stocks that are more integrated. With this reasoning, we use the pooled sample in this study rather than evaluating each of the 24 emerging markets separately.

Our preliminary results on market anomalies reveal that the size effect is not significant in high book-to-market (B/M) and aggressive investing stocks, consistent with FF's (2015) findings. Anomalies regarding the profitability, B/M, and investment effects, are more notable once Ajili's (2002) method for average portfolio calculation is used. However, small-profitability sorted portfolios showed no distinct profitability effect. This suggests that, though less pronounced than in developed markets, emerging markets display key anomalies identified in the empirical literature, even when controlling for country-specific risks in test portfolios through diversification. Considering the risk premiums, we find significant premiums for value (HML), profitability (RMW), and investment (CMA) factors, unlike the insignificant size (SMB) risk premium. In contrast to Mosoeu and Kodongo (2022), our findings indicate a positive market equity premium in the examined emerging markets, albeit it is not statistically significant. The value premium, though higher than in the developed markets, was lower than in Eastern European emerging markets, as documented by Zaremba and Czapkiewicz (2017). These findings align with FF's (2017) findings in the Asia Pacific region. Our findings also echo the trend of statistically insignificant size and market premiums in emerging markets, which is a common issue in these markets (Azimli, 2020).

Considering the asset pricing performance of the CAPM, FF3, and FF5 models, our findings indicate that none of the models can produce insignificant alphas across all portfolio sorts, suggesting a failure to fully capture the variation in the test portfolios. This is in line with FF (2015, 2017), Zaremba and Czapkiewicz (2017), and Mosoeu and Kodongo (2022). Notably, the FF3 and FF5 models outperform the CAPM, particularly in

[3] This is similar to ours with the exception of Russia and Saudi Arabia. Our dataset excludes Russia whereas theirs exclude Saudi Arabia.

B/M and investment-sorted portfolios, with FF5 showing superior performance in most of the employed performance metrics. This result is consistent with the findings of FF (2017), across various regions, highlighting the improved efficacy of FF models, especially when including RMW and CMA factors. After finding the FF5 model minimizes the pricing errors, GEPU was added to this model, and the augmented FF5 is evaluated. We find that adding GEPU factor to the FF5 did not improve the FF5 in B/M portfolios and profitability-sorted portfolios. However, a minor improvement is observed in investment-sorted portfolios, marked by modest decreases in absolute intercepts and improvements in other metrics, albeit not of major economic significance. Although previous literature finds significant risk premiums for policy uncertainty which implies the GEPU should have an incremental explanatory power in the asset pricing tests, (Brogaard &Detzel, 2015; Chiang, 2019; Lam et al., 2018, Brogaard et al., 2020) our findings suggest that FF (2015) risk factors subsume the explanatory power of the GEPU. Our results are also robust to the choice of policy uncertainty measures.

Our contribution to the extant literature can be summarized in two aspects. First, the existing body of literature identifies and substantiates a significant correlation between economic policy uncertainty and stock return dynamics. However, previous research in this domain has predominantly been limited to examining U.S. stock equities, as shown in studies by Brogaard and Detzel. (2015) and Bali et al. (2017). Additionally, prior investigations have concentrated on stock indices (Antonakakasi et al., 2013), specific emerging markets (Li, 2017; Yang et al., 2019), industry-specific portfolios (Hu et al., 2018), regional markets (Aslanidis et al., 2023; Chiang, 2019), specific industrial sectors (Maquieira et al., 2023; Azimli, 2022), and a selection of few emerging markets (Das and Kumar 2018; Lam et al., 2018). Our research diverges from these previous studies by integrating a broad range of emerging market equities possibly used by international investors for diversification. Second, our study covers a more recent period hosting influential world events (the COVID-19 pandemic and the Russia-Ukraine war) that can significantly increase global economic policy uncertainty. Further, our paper tests the Fama-French Five-Factor (FF5) model's applicability in emerging markets. By applying the FF5 model to a diverse array of emerging markets with the latest data, our study provides novel insights into its effectiveness in different market conditions. This aspect of our research is particularly pertinent for portfolio managers and investors, and we have discussed its implications in the concluding section of our paper.

The organization of our study is as follows. Following the Introduction, Section 2 offers a brief literature review of relevant studies. Section 3 describes our data and methodology, including the test portfolio and risk factor formations. Section 4 presents the summary statistics for test portfolios and factors and Section 5 reports the results of the asset pricing tests. Section 6 conducts several robustness checks to see if our policy uncertainty proxy is sensitive to variable selections. Finally, Section 7 contains the conclusion.

2. Theoretical background and literature review

2.1. CAPM's deficiency and factor models of Fama – French

Empirical studies of the CAPM often rely on a value-weighted portfolio consisting of all stocks as a reliable proxy for CAPM's market portfolio. However, the CAPM assumes that the market portfolio includes all available investments, including shares, bonds, real estate, and even human capital (see Roll, 1977, Jagannathan and Wang, 1993). The Arbitrage Pricing Theory (APT) of Ross (1976) addresses the critique regarding the unobservable nature of the market portfolio. APT hypothesizes systematic risk should be multidimensional where more than one factor can capture multiple systematic risk sources. Nevertheless, Gilles and LeRoy (1991) criticized the applications of APT for lacking the guidance based on economic theory on picking from k number of systematic factors making the analogy of a "fishing net of factors".

The emergence of anomalies in the literature further challenged the applicability of the theoretical market portfolio of CAPM (see Osterierder and Seigne, (2023) for a comprehensive review)[4]. After investigating the vast universe of anomalies literature, FF formulated the three and five-factor models (FF 1993, 2015) that reduce CAPM's estimation error by capturing the multidimensionality of the systematic risk. Authors add factor mimicking portfolios for size (SMB), value (HML), profitability (RMW), and investment (CMA) anomalies to the empirical form of the CAPM. The non-diversifiable systematic risk associated with the size was hypothesized to be due to downturn and liquidity risk, while the value factor is primarily due to financial distress risk (FF, 1993). The authors utilize the implications of the dividend discount model to support their factors with financial theory (FF, 2015) in relation to the profitability and investment aspect of the non-diversifiable systematic risk.

FF (2015) shows that FF5 improved the pricing performance of its predecessors (FF3 and CAPM) for equities quoted in NYSE, NASDAQ, and AMEX from 1963 to 2013. FF (2017) provided out-of-sample tests for the model's explanatory power in developed markets of Europe, Japan, and Pacific Asia to address MacKinley's (1995) data snooping issues. They conclude that the model outperforms FF3 and CAPM. Nonetheless, the dynamics of emerging stock markets differ from those of developed economies, as Rajeb et al. (2015) noted. Lin (2017) tested the model for Chinese stock markets, which yielded similar results to FF (2015); Singh and Tripathi (2020) undertake further tests for the Indian stock exchange, finding the model had higher explanatory power for stocks quoted in CNX 500. Zaremba and Czapkiewicz (2017) test the model for over 100 anomalies in five Eastern European emerging markets (Czech Republic, Hungary, Poland, Russia, and Turkey). They find that FF5 outperformed FF3 and CAPM in explaining the cross-sectional returns. Nevertheless, 20 capitalization-weighted portfolios yielded significant alphas, implying the model could not price all the returns. Azimli (2020) tested the model for stocks quoted in Borsa İstanbul, comparing its performance with the FF3, CAPM, and Q-factor models. The author finds that FF3 performs better than other models, and RMW and CMA factors do not add significantly to the explanatory power of FF3 in explaining the cross-section of returns for stocks quoted in the Borsa İstanbul.

2.2. Role of economic policy uncertainty in stock returns

A common theme for emerging markets is argued to be higher political uncertainty and geopolitical risk (Zaremba et al., 2022). Unexpected changes in governments' economic policies can significantly affect asset prices through at least two channels (Azimli, 2022). First, intertemporal choices of firms and consumers on saving, consumption, and investment can vary due to shocks in economic policies. Second, high policy uncertainty would lead to higher inflation rates, eventually leading investors to adjust their earnings forecasts, raise their discount rates, and, therefore, require higher risk premiums on their investments (Pastor & Veronessi, 2012). Utilizing the aforementioned theoretical aspects, Pastor and Veronessi (2012) derived a general equilibrium model that implies a negative relationship between stock prices following a policy shock and an unanticipated policy change. Influenced by this foundation, Baker et al. (2016) devised an index to assess the impact of economic policy uncertainty (EPU) on the government's monetary, fiscal, and regulatory choices. They have shown that there is a strong relationship between the EPU index, stock market volatility, and returns in the US. Specifically, there is a notable (positive) negative correlation between the EPU index and stock market returns (volatility).

Antonakakis et al. (2013) empirically support Pastor and Veronessi's (2012) model implications. The authors show for stocks quoted in the S&P500, the negative relation

[4] Size effect (Banz 1981), value effect (Rosenberg, Leid and Lanstein 1985), Jagadesh and Titman's (1993) momentum anomaly, Profitability effect (2013), asset growth effect (Cooper, Gulen & Schill, 2008), and investment anomaly (Titman, Wei and Xie, 2004) were among the most empirically debated anomalies.

between stock returns and policy uncertainty is consistent from 1985-2013. Their results were robust to the choice of uncertainty index as well. In a follow-up paper, Pastor and Veronessi (2013) show that EPU commands a significant risk premium in weak economic cycles, they further claim that unverifiable nature of the government-induced uncertainty is a systematic risk source. Nevertheless, they do not account for the known risk factors that could have subsumed the macro-built EPU variable. Brogaard and Detzel (2015) address this issue by controlling for market risk and additional risk factors proposed by FF (1993) and Carhart (1997) by utilizing factor-mimicking portfolios for known anomaly variables; size, value, and momentum. They find that even after controlling for the known risk factors, EPU generated a significant negative risk premium leading them to conclude that EPU is an undiversifiable systematic risk in the US equity markets. Authors argue that although the market factor captures the systematic risk related to market uncertainties, economic policy uncertainty-related risk was not captured by any of the FF factors and market portfolio. Bali et al. (2017) on the other hand, showed that after controlling for five risk factors[5], policy uncertainty generated significant premiums in the US equity markets.

In terms of international evidence, Lam et al. (2018) who studied 49 international equities and controlled for the FF (1993) three factors, find that policy uncertainty is an undiversifiable risk in international markets that earn a risk premium. Lam et al. (2018) hypothesize that government stability and bureaucracy quality were two factors that were the underlying cause of GEPU risk where they find the bureaucracy quality factor-mimicking portfolio subsumes the GEPU risk. Aslanidis et al. (2023) argue that in the spirit of factor asset pricing models, market risk premium and GEPU premium should not reflect the same systematic risk factors since they have opposite signs[6] and they both remain significant in their tests on international markets. Brogaard et al. (2020) find that there is a significant relation between the GEPU risk and changes in the discount factor. This leads to an increase in investors' risk aversion and prompts them to diversify away from safer assets (like bonds). This may explain the presence of a negative risk premium on the high GEPU stocks as reported in the literature. Luo and Zhang (2020) argue that policy uncertainty proxies for stock crash risk that is not captured by conventional risk factors. Kundu and Paul (2022) studied the EPU stock return relationship among G7 countries. They find that increased EPU causes a decline in stock returns due to increased market volatility. However, this effect is present only in contemporaneous periods and when the market conditions are bearish. Similarly, Chieng (2019) who studied G7 countries illustrates that stock returns are negatively related to both local and global economic policy uncertainty. On the contrary, Azimli (2022) tested the EPU shock hypothesis by controlling for risk factors of FF5 using 49 industry portfolios for AMEX, NYSE, and NASDAQ. The author shows that only 15 portfolios had significant loadings on EPU, whereas the EPU index cannot improve the explanatory power of the FF5. Under the implications of the Efficient Market Hypothesis (EMH) Azimli's (2022) work can be interpreted in two ways. First, although the correlation between EPU and FF's risk factors was low[7], five factors might have captured the undiversifiable risk related to the EPU in US stock markets. Second, unanticipated shocks in economic policy are idiosyncratic rather than systematic risks priced with premiums.

Concerning emerging markets, the negative effect of EPU on stock market returns is also corroborated by Xu et al. (2021), Chieng (2019), Das and Kumar (2018), Li (2017), and others. Xu et al. (2021) study the EPU stock return relationship in the Chinese A-share market from 2005-2020. The authors show a negative relationship between returns and EPU, and the index has significant predictive power in the Chinese A-share market. Das

[5] Which include return on equity as profitability factor in addition to size, value market and momentum factors.

[6] Unlike GEPU premium, market risk premium is positive.

[7] Market, size and value factors had negative correlations of -0.12. -0.01. and -0.06 respectively whereas RMW and CMA was positively correlated with EPU with 0.08 and 0.02.

and Kumar (2018) followed a wavelet coherence methodology to investigate the implications of policy uncertainty on returns of 11 developed and six emerging markets. The authors' findings align with the negative return EPU shock hypothesis for developed and emerging markets. However, while developed markets are significantly affected by both US EPU and domestic EPU indices, emerging markets' stock returns are affected by domestic measures of EPU, implying they are less vulnerable to international policy shocks. Moreover, the study demonstrated that within the framework of developed markets, Japan and European countries are solely influenced by the EPU originating from the US, remaining unaffected by their respective domestic EPUs. In contrast, the findings of Li (2017) contradict the current research, providing a distinct viewpoint on emerging markets. The authors demonstrated that in the Chinese equity markets, the risk associated with EPU carries a significant positive risk premium. This is attributed to the market being predominantly influenced by speculative traders. This outcome persisted even after accounting for the market portfolio and FF variables.

3. Data and methodology

3.1. Data bases

Two data sets are employed to undertake this research: Global Economic Policy Uncertainty (GEPU) Index data and monthly value-weighted adjusted[8] returns of stocks quoted in emerging markets. Our data are monthly time series spanning from January 1997 to May 2023. GEPU Index data is gathered from Baker, Bloom, and Davis' database (see https://www.policyuncertainty.com/). For monthly value-weighted returns of test assets, the portfolio return data is collected from Kenneth French's[9] database who construct the portfolios using Bloomberg data. Test assets contain stocks of Brazil, Chile, China, Colombia, Czech Republic, Egypt, Greece, Hungary, India, Indonesia, Malaysia, Mexico, Pakistan, Peru, Philippines, Poland, Qatar, Saudi Arabia, South Africa, South Korea, Taiwan, Thailand, Turkey, United Arab Emirates. The monthly returns of emerging market portfolios, FF (2015) factor returns, and the risk-free rate (monthly US T-Bill rate) are all obtained from Kenneth French's database. The return data is in US dollars to tackle the synthetic increases in stock prices due to the devaluation of currencies faced by some of the emerging markets in our sample.

3.2. Test portfolios

The basis for not working on firm data and specific country data is that in such a case, idiosyncratic elements (residuals of the model) would contain firm or country-specific risks and might not average to zero. This is against the spirit of our study since we try to isolate idiosyncratic risk, and explain the expected variations and the cross-section of average returns in emerging markets due to systematic risk. Nevertheless, portfolios sorted in a 2x3 manner are employed as test portfolios. The portfolios are sorted in line with FF (1993, 2015, 2017). Size, B/M ratio, operating profitability (OP), and Investment (measured as growth in total assets) characteristics are utilized to sort the portfolios. Portfolios are sorted into two size groups and three other characteristic groups. Portfolios for the period t are formed using the characteristic data of June of year t since accounting information is subsumed by the market for year *t*-1 in this period (FF 1993, 2015). Next, the value-weighted excess returns of the portfolios are calculated, every year, portfolios are rebalanced following the same procedure.

To sort for firm size, firms' market capitalization data for each country are put in ascending order in June of year *t*; the 90th percent percentile is used as the breakpoint. The top 90 percent are considered big, and the bottom 10 percent are grouped as small stocks. For B/M, OP, and Investment, stocks are allocated into three groups using the 30th

[8] Returns include dividends and capital gains, and are not continuously compounded.
[9] See https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html.

and 70th percentiles as breakpoints. The first group of each set comprises stocks within the bottom 30th percentile. For the B/M sorted set, this segment is populated with low B/M stocks. However, this section includes firms with a conservative investment approach and weak profitability in the investment and OP sorted sets. The second division in each set encompasses the 40th percentile. In the B/M set, these stocks represent companies with medium B/M ratios. These groups are characterized by firms with neutral investment and OP in the investment and OP categories. The final group, which contains the remaining stocks within the top 30th percentile, includes firms with high B/M ratios in the B/M group, aggressively investing firms in the investment group, and companies with strong profitability in the OP group.

After the sorting procedure, two sets of firms grouped with respect to their size and nine sets of firms grouped with respect to their investment levels, OP, and B/M ratio levels are formed. By taking the intersections of each group, three sets of six 2x3 sorted, a total of 18 portfolios are constructed. Firms with negative B/M ratios in the portfolio formation period are excluded from the sample. In addition, firms with missing data for at least one of the following; cost of goods sold, selling, general and administrative expenses, or interest expense for *t*-1 and total assets data for *t*-2 and *t*-1 of the portfolio formation date were excluded. Our study's methodology, which necessitated the exclusion of firms with incomplete financial data, may have introduced survivorship bias. This concern, highlighted by Elton, Gruber, and Blake (1996), is particularly pertinent in emerging markets where data inconsistencies are more prevalent (Bekaert and Harvey, 2000). In these markets, the exclusion of firms due to data unavailability could lead to an overrepresentation of more stable firms, potentially skewing results. Table 1 illustrates the intersections used in the portfolio formation procedure.

Table 1. Portfolios formed with the intersection of two size, three B/M, or Operating profitability, or Investment level.

Other Characteristics		B/M Ratio			Operating Profitability			Investment level		
		Low	Medium	High	Weak	Neutral	Robust	Conservative	Neutral	Aggressive
		(L)	(M)	(H)	(W)	(N)	(R)	(C)	(N)	(A)
Size	Small (S)	SL	SM	SH	SW	SN	SR	SC	SN	SA
	Big (B)	BL	BM	BH	BW	BN	BR	BC	BN	BA

Note. The table provides a visual representation of the intersections between two categories of size and three other groups of characteristics, specifically the book-to-market equity ratio, operating profitability, and investment levels. The table displays a total of 18 portfolios that have been derived from the intersections of various sizes and other characteristic groupings. In terms of magnitude, the 10th and 90th percentiles were employed as the division points, while for the remaining three attributes, the 30th and 70th percentiles were utilized as the breakpoints.

3.3. Factors

The risk factors employed in this study are FF's (2015) factor mimicking portfolios. These are hedge portfolios with long positions in firms with the characteristics that earn a premium and short positions in firms with the opposite characteristics holding other features roughly constant. For instance, SMB is a hedge portfolio with a long position in small-cap stocks and a short position in large-cap stocks, holding approximately constant OP, investment, and B/M levels.

The market factor is the excess returns of this portfolio to the risk-free rate. Other risk factors are constructed using adjusted returns of eighteen 2x3 sorted portfolios illustrated in **Table 1**. Table 2 summarizes the formation of FF risk factors. All three sets of six portfolios are formed with size and one other characteristic. Therefore, constructing a size factor (SMB) that reflects only the size effect but not the other characteristics, three SMB factors are created, and their average monthly returns are used. Table 3 illustrates the formation of the SMB factor.

Table 2: Factor calculation

Sort	Breakpoint	Calculation
2x3	---	MKT= value-weighted portfolio of all stocks
2x3	Size; 10th and 90th percentiles	$SMB = \frac{(SMB_{B/M} + SMB_{O/P} + SMB_{\triangle TA})}{3}$
2x3	B/M; 30th and 70th among big	$HML = \frac{(SH + BH)}{2} - \frac{(SL + BL)}{2}$
2x3	OP; 30th and 70th among big	$RMW = \frac{(SR + BR)}{2} - \frac{(SW + BW)}{2}$
2x3	oTA; 30th and 70th among big	$CMA = \frac{(SC + BC)}{2} - \frac{(SA + BA)}{2}$

Note: This table illustrates the factor formation procedure for period *t*. Excess returns of portfolios explained were used to form the factors.

Table 3: Derivation of the SMB factor

Sort	Breakpoint	Calculation
2x3	Size; 10th and 90th percentiles B/M; 30th and 70th among big	$SMB_{B/M} = \frac{[R_t(SL) + R_t(SM) + R_t(SH)] - [R_t(BL) + R_t(BM) + R_t(BH)]}{3}$
2x3	Size; 10th and 90th percentiles OP; 30th and 70th among big	$SMB_{OP} = \frac{[R_t(SR) + R_t(SN) + R_t(SW)] - [R_t(BR) + R_t(BN) + R_t(BW)]}{3}$
2x3	Size; 10th and 90th percentiles oTA; 30th and 70th among big	$SMB_{\triangle TA} = \frac{[R_t(SC) + R_t(SN) + R_t(SA)] - [R_t(BC) + R_t(BN) + R_t(BA)]}{3}$
		$SMB = \frac{(SMB_{B/M} + SMB_{O/P} + SMB_{\triangle TA})t}{3}$

Note: In order to capture the size effect independent from value, profitability, and investment effects, three SMB factors were formed. Then their arithmetic average is taken. The table illustrates the formation procedure for period *t*.

3.4. GEPU Index

Measuring uncertainty can be challenging (Gulen & Ion, 2016). The GEPU index of Baker et al. (2016) is a news-tracking index that tracks a weighted average of three main components: news related to economic uncertainty, possible changes in tax code, and news related to the uncertainty of future fiscal and monetary policy in selected newspapers of each country. The GEPU index is the weighted average of national EPU indices of 21 countries.[10]. The construction of the GEPU Index involves a three step procedure. Initially, each country's EPU index is re-normalized to a mean of 100 from 1997 to 2023. Then, missing data for specific countries is estimated through a regression-based methodology, resulting in a comprehensive monthly EPU index set for 21 nations beginning from January 1997. Lastly, the monthly GEPU Index is calculated as the GDP-

[10] Australia, Brazil, Canada, Chile, China, Colombia, France, Germany, Greece, India, Ireland, Italy, Japan, Mexico, the Netherlands, Russia, South Korea, Spain, Sweden, the United Kingdom, and the United States.

weighted mean of the 21 individual EPU indices, using the GDP information sourced from the IMF's World Economic Outlook Database.[11]

Figures 1 and 2 illustrate the time-series data of the GEPU index and monthly changes in the index from January 1997 to May 2023, respectively. As seen from the figures, index data shows a tendency to spike at significant events likely to cause a change in economic policy. For instance, the index spiked in 2008 around Bearn Stern's rescue loan and Lehman's bankruptcy. This was followed by the Eurozone Debt crisis in 2011 and the European immigration crisis in 2016 with eastern Aleppo's fall in Syria. Spikes around June 2016 are also visible where the Brexit referendum took place. Both the time series and change of the index exhibit spikes around March 2020 and March 2022, which are the dates that correspond to the COVID-19 pandemic outbreak and the beginning of the ongoing Russian Ukrainian conflict. Considering the index of Baker et al. (2016) capture the variation in significant global events that lead to shifts in economic policy, we employ the monthly changes in the index as a proxy for international economic policy uncertainty. In the following sections, we subjected this choice to a number of robustness controls.

Figure 1: The figure illustrates the time series trend of the GEPU index

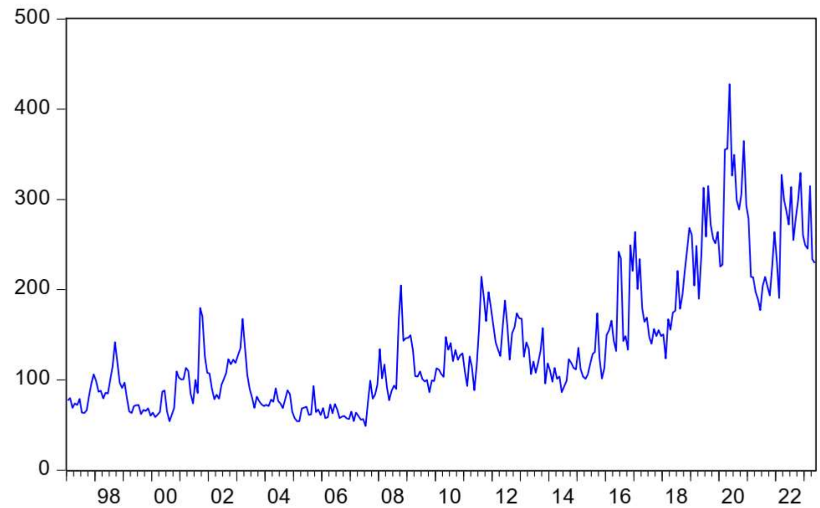
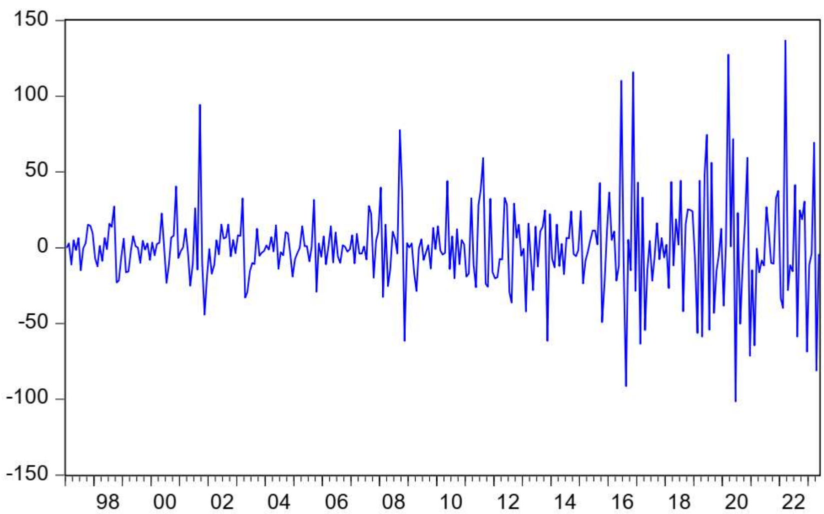


Figure 2: The figure illustrates the time series trend of the change in the GEPU index which is calculated by taking the first difference of GEPU index; $\Delta GEPU_t = GEPU_t - GEPU_{t-1}$



[11] Readers can visit https://www.policyuncertainty.com/global_monthly.html for detailed explanation of the index.

3.5. Methodology

In our analysis, monthly changes in the GEPU index and FF (2015) factors are regressed on the value-weighted returns of 18 emerging market portfolios. The base model has the form:

$$R_{i,t} - R_{rf,t} = \alpha_i + \beta_i\left(R_{m,t} - R_{rf,t}\right) + S_i + SMB_t + h_i HML_t + r_i RMW_t + c_i CMA_{t_{g_i}} \triangle GEPU_t + \varepsilon_{i,t}. \quad (1)$$

In Equation 1, Ri indexes return on 18 portfolios, Rm is value-weighted monthly returns of the portfolio of all stocks in the sample, Rf is the 1-month US T-bill rate, SMB, HML, RMW, and CMA are FF factors for size, value, profitability, and investment respectively (see Section 3.3). ∆GEPU is the monthly change in the GEPU index, $\varepsilon_{i,t}$ is the residuals with an expected value of zero, and α_i is the intercept term. The R_m – R_{rf}, SMB, HML, RMW, and CMA are risk factors that require premiums (FF, 2015). β_i , s_i, h_i, r_i, c_i, and g_i are the loadings on the risk factors and the changes in the GEPU index. Our main goal is to test whether αi remains significant in the presence of other coefficients for any *i*.

At first, we estimate **Equation 1**, along with CAPM, FF3, and FF5 in their empirical form. Then, following FF (2015) and Azimli (2020), six performance metrics are used to test the performance of CAPM, FF3, and FF5, along with the base model. First, Gibbons, Ross, and Shanken's (1989) GRS test statistic is employed. The test evaluates whether the intercepts of the portfolios are jointly insignificant. The second, the absolute intercept value, is used ($A.|\alpha_i|$); a smaller value is preferred since it minimizes the unexplained returns. Third, average absolute standard errors are employed ($A.$ (α_i)); a lower value is preferred. Fourth, the absolute dispersion of intercept estimates relative to the average absolute portfolio excess returns minus the average V-W market return is adopted. ($\frac{A.|\alpha_i|}{A.|r_i|}$) The market portfolio as a reference point is appropriate since it corporates the stocks entirely in the sample (Azimli 2020). Fifth, a squared version of ($\frac{A.|\alpha_i|}{A.|r_i|}$) is utilised. Sixth, an adjusted coefficient of determination that shows the model's fit; a higher value is preferred (R^2). Lastly, the ratio of the average value of standard errors of the intercepts to the average value of squared intercepts ($\frac{A.s^2(\alpha_i)}{A.\alpha_i^2}$).This metric measures the dispersion fraction attributable to the sampling errors. **Table 4** summarizes these metrics.

Table 4: The table illustrates the performance metrics adopted in the study to evaluate the pricing performances of the models.

Performance Metric	Explanation
GRS Test	Gibbons Ross and Shanken's GRS test statistic
$A.\|\alpha_i\|$	Average Absolute Value of the İntercept
$A.s(\alpha_i)$	Average standard errors of the intercepts
$\frac{A.\|\alpha_i\|}{A.\|r_i\|}$	The ratio between the average value of the intercept and the average absolute value of the difference between average excess portfolio returnsand average value-weighted portfolio returns.
$\frac{A.\alpha_i^2}{A.r_i^2}$	The ratio of average value of intercept to average absolute value of average excess portfolio returns minus average value-weighted portfolio returns squared
$\frac{A.s^2(\alpha_i)}{A.\alpha_i^2}$	The ratio between the average squared value of standard errors of intercepts in the models and the average squared value of intercepts.
$A(R^2)$	Average adjusted coefficient of determination

OLS estimators will not be efficient if the residuals are not normally distributed with a mean of zero (Woolridge, 2001). To tackle this issue we use autocorrelation and heteroscedasticity-adjusted residuals (Newey & West, 1987) and undertake robustness checks in Section 5 by using alternative measures of the GEPU index.

4. Summary statistics

4.1. Test portfolios

The average excess returns of 2x3 sorted test portfolios are presented in **Table 5**. The test portfolios are diversified portfolios that contain all the stocks available in Bloomberg data for 24 emerging markets (see data explanations at https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/Data_Library/six_portfolios_emerging.html). Hence, by accounting for size and one additional characteristic, we can assess whether the average stock return patterns documented in the literature apply to emerging markets.

Considering **Table 5**, the size effect is apparent only in high B/M portfolios for portfolios sorted concerning their size and B/M equity. In this group, small firms earn 0.34% more on average every month than large firms. However, small-cap stocks earn 0.60% lower in the low B/M group, whereas in the medium group, they earn 0.15% lower relative to the large-cap stocks. FF (2015) documented the same issue in the lowest B/M quantile. Eraslan (2013) also report a reverse size effect in low B/M groups. When portfolios are sorted with respect to their size, investment, and operating profitability levels, the size effect was evident in both low and medium groups. Nevertheless, there is no evidence of the size effect in high groups (aggressive investing and robust profitability). In size, operating profitability sorts, small weak and small medium profitability portfolios earn 0.17% and 0.29% higher on average, respectively, relative to their large-cap counterparts. In contrast, in terms of size investment sorts, small conservative and small neutral portfolios outperform their large-cap counterparts by 0.07% and 0.19%, respectively.

Table 5. The table illustrates the average monthly excess returns and standard deviations of these returns of the test portfolios for the period spanning from January 1997 to May 2023.

	Low	Medium	High	Low	Medium	High
Panel A: Size-B/M portfolios	Average Excess Return			Standard deviation of excess returns		
Small	0.0077	0.5657	1.2072	6.2152	5.8862	5.9393
Big	0.6111	0.7120	0.8706	6.1317	6.4641	6.6544
Panel B: Size-OP portfolios						
Small	0.6805	0.9134	0.7615	6.0326	5.9078	5.8659
Big	0.5104	0.6200	0.8364	6.6662	6.2976	6.1737
Panel C: Size-Investment portfolios						
Small	0.9016	0.8669	0.4262	5.8127	5.8506	6.2596
Big	0.8286	0.6753	0.6231	5.9694	6.2256	6.8814
Panel D: Average Portfolios	Average Excess Return			Standard deviation of excess returns		
Characteristic	BE/ME	Profitability	Investment	BE/ME	Profitability	Investment
Low	0.3094	0.5955	0.8651	6.0358	6.2438	5.7674
High	1.0389	0.7990	0.5246	6.2107	5.8878	6.4569

Note. The derivation of these test assets is discussed in Section 3. Low, Medium and High imply weak, neutral and robust profitability for Size-Operating profitability (OP) sorted portfolios whereas they imply Conservative, Neutral and Aggressive for Size-Investment sorted portfolios. Average portfolios are formed following Ajili (2002). These portfolios are constructed using arithmetic averages of either two high (aggressive for investment, robust for profitability) or low (conservative for investment, weak for profitability) groups. For instance, the high investment portfolio is derived by calculating the returns in each month t as; (BA+SA)/2. Then the average and standard deviation of this new portfolio are calculated and presented in the table.

Following Ajili (2002), two additional portfolios are constructed to examine the return patterns in broader terms. Mean returns of two high and two low groups are taken to construct the new "average portfolio". For instance, high profitability in Panel D of **Table 5** represents the average of two robust profitability portfolios (SR and BR).

Considering average portfolios, once the neutral portfolios are not accounted for, operating profitability, B/M, and expected investment patterns are reflected in the average returns of the emerging markets. Portfolios with high B/M and robust profitability characteristics outperform low B/M and weak profitability portfolios by 0.73% and 0.20%, respectively, whereas conservative investing stocks earn 0.34% higher than stocks with aggressive investment characteristics.

4.2 Fama and French factors

Results in Panel A of **Table 6** indicate that factors other than Rm-Rf and SMB are significant at a 1% and 5% significance level, respectively. Value factor (HML), profitability factor (RMW), and investment factor (CMA) yield statistically significant premiums of 0.73%, 0.20%, and 0.34% monthly. The size risk premium measured by the SMB factor is relatively low (0.0048 percent), which aligns with Azimli (2020), who found an insignificant size risk factor in Borsa Istanbul – Turkey. Contrary to the findings of Mosoeu and Kodongo (2022), who examined eight emerging markets, our research indicates a positive market equity premium that is both larger in magnitude and exhibits a greater standard deviation. This implies higher risk aversion in the emerging markets we examine. Value premium measured by the HML factor is found to be economically higher than North America, Europe, Japan and the U.S. (FF, 2017). However, in comparison to the emerging markets in Europe, our value premium is approximately 50 basis points lower with almost similar standard deviation (Zaremba & Czapkiewicz, 2017), implying eastern European emerging markets require higher premiums or they have higher reward-to-volatility ratios.

Table 6: The table illustrates the summary statistics of FF's risk factors.

2x3 Factors					
	Rm-Rf	SMB	HML	RMW	CMA
Panel A	Average Returns, t-statistics and standard deviations of factors				
Mean	0.53	0.0048	0.73	0.20	0.34
t-stat.	1.27	0.04	4.47***	2.49**	2.91***
SD	6.16	1.96	2.26	1.43	1.82
Panel B	Correlation Matrix of Factors				
Rm-Rf	1.00				
SMB	-0.31***	1.00			
HML	0.06	0.05	1.00		
RMW	-0.21***	-0.16***	-0.47***	1.00	
CMA	-0.38***	0.10*	0.38***	-0.11*	1.00

Note: *** indicates statistical significance at the 1% level, ** indicates statistical significance at a 5% level and * is for significance at the 10% significance level. The t-statistics are adjusted for autocorrelation with Newey and West's (1987) methodology. Panel A reports the arithmetic mean of the factor returns, t-statistics of the null hypothesis the mean being zero, and standard deviations. Panel B reports the correlations.

Table 6 illustrates that RMW and CMA premiums are significant at a 1% significance level. Considering FF's (2017) findings, our RMW and CMA premiums are closest to the Asia Pacific region's premiums. Our CMA premium is five basis points lower whereas our RMW premium is only one basis point lower than FF's findings. However, FF (2017) only find CMA to be statistically significant, with a 5% significance level. In line with our findings, Zaremba and Czapkiewicz (2017) also find RMW to be a statistically significant risk factor with a premium of 0.73%, which is 53 basis points higher than our finding.

Similar to Azimli (2020), Mosoeu and Kodongo (2022), Zaremba and Czapkiewicz (2017), and FF (2017), we find size factor and market premiums to be statistically indistinguishable from zero. This is a common problem in emerging markets (Azimli, 2020). **Table 6** shows that SMB has a mean value of 0.0048% and is only 0.04 standard error from zero due to a 1.96% monthly standard deviation. Although the market proxy presents an economically meaningful premium consistent with emerging market literature, its t-value of 1.54 (with a p-value of 12.56%) does not achieve statistical significance at conventional levels.

5. Model performance tests

5.1 Performances of benchmark models

In this section, we compare the pricing performances of CAPM, FF3, and FF5 for 18 portfolios sorted according to their size, book-to-market value, investment level, and operating profitability. The construction of these portfolios is described in detail in **Section 3**.

The empirical form of the augmented version of FF5 is presented in sub-section 3.4. FF (2015) argue that a complete asset pricing model should yield intercepts indistinguishable from zero with such regression specification. We formally test the null hypothesis H_0: = $\alpha_1 = \alpha_2 = \alpha_3 = \alpha_4 \dots \alpha_n = 0$. Nevertheless, the GRS test depends on the assumption of homoscedasticity and no auto-correlation in residuals.

Table 7: The table presents the performance metrics of CAPM, FF3 and FF5 in explaining the test assets.

Models	GRS	$A.\lvert\alpha_i\rvert$	$A.s(\alpha_i)$	$\frac{A.\lvert\alpha_i\rvert}{A.\lvert r_i\rvert}$	$\frac{A.\alpha_i^2}{A.r_i^2}$	$\frac{A.s^2(\alpha_i)}{A.\alpha_i^2}$	AR²
B/M Portfolios							
CAPM	44.85*	0.31	0.11	1.02	1.05	0.09	0.92
FF3	36.76*	0.22	0.05	0.74	0,54	0.04	0.98
FF5	32.89*	0.22	0.06	0.71	0,50	0.05	0.98
OP Portfolios							
CAPM	34.07*	0.22	0.09	1.15	1.32	0.12	0.94
FF3	39.21*	0.23	0.06	1.18	1.39	0.04	0.98
FF5	28.64*	0.16	0.05	0.79	0.63	0.06	0.99
Inv Portfolios							
CAPM	33.82*	0.24	0.10	1.06	1.11	0.12	0.93
FF3	26.00*	0.19	0.07	0.83	0.70	0.11	0.97
FF5	23.96*	0.17	0.05	0.76	0.57	0.06	0.99

Note. The sample covers the period from January 1997 to May 2023. Symbols ** and * represent statistical significance at 5% and 1% respectively.

The first column of **Table 7**, the GRS statistics are presented for three competing asset pricing models. The models fail to provide insignificant intercepts for all portfolio sorts, implying the models fail to explain the shared variation in considered portfolios. All the GRS test statistics are found to be significant at a 1% significance level. Our findings align with FF (2017), who find significant joint intercepts for Europe, North America, and Asia Pacific equity markets. Mosoeu and Kodongo (2022) also find that FF5 fails to produce statistically insignificant alphas when considered jointly in emerging markets. Azimli (2020), on the other hand, show that FF5 produces significant intercepts only in B/M sorted portfolios in Borsa Istanbul, whereas, for portfolios with different characteristics, the null hypothesis of GRS tests failed to be rejected. From the reviewed literature, it could be argued that when emerging market data is pooled, the model fails to generate insignificant alphas. In contrast, country-specific created factors tend to improve the jointly significant alpha problem for that specific country's equity markets. It would be interesting to test each emerging market with its country-specific data.

The GRS test provide information on the joint significance of the alphas; however, economic sense cannot be made with these tests. Following FF (2017), we adopt several other metrics explained in **Section 4**. Considering B/M and investment-sorted portfolios, CAPM is outperformed by FF3 and FF5 models in every metric. However, in OP portfolios, CAPM produces lower average alphas and a lower intercept dispersion relative to the market excess returns compared to the FF3. Nevertheless, in an economic sense, these effects are negligible for these metrics. [12] FF (2017) show that FF5 outperformed FF3 in every region apart from Europe. All the metrics yielded qualitatively similar results for B/M sorted portfolios in Europe. We also find that in B/M sorts, FF3 and FF5 had similar performances in pricing equities, indicating that the emerging markets we are evaluating have similar dynamics to European markets when collectively assessed. The average absolute intercepts yielded by both models are found to be 0.22 FF5, producing only 0.01 higher average absolute standard errors.

Including RMW and CMA factors in the FF3 improves the pricing of OP-sorted portfolios. Absolute average intercepts diminish by seven basis points, and the dispersion metric reduces by 0.39. In addition, the model provides lower absolute standard errors for intercepts. This finding aligns with FF (2017), who also find that FF5 outperform FF3 in every metric for size-OP sorted portfolios in North America, Europe, Japan, and Asia Pacific markets.

In investment portfolios, however, FF5 outperforms FF3 in every metric with a lower magnitude. For instance, the model reduces the value of average absolute intercepts and their standard errors only by 0.02%. Nevertheless, when the dispersion metric is considered, the model prices investment portfolios and OP-sorted portfolios better since this metric is also reduced by seven basis points relative to the FF3.

5.2 Performance of the augmented model

In this section, we include the first difference of the GEPU index introduced in Section 3.3 to the FF5 and then test the performance of the model in explaining the cross-sectional variation in returns due to size, B/M, investment, and OP.

Although the GRS test statistic rejects FF5 and its' augmented version, **Table 8** offers noteworthy results for FF5's pricing performance in emerging markets. First, including $\Delta GEPU_t$ did not improve FF5 in explaining the returns of B/M portfolios. All the metrics yield quantitatively the same results with FF5. In addition, only small and medium B/M level portfolio had significant exposure to ΔGEPU, whereas big-neutral portfolio in investment sorted portfolios and small-high profitability portfolio in profitability sorted portfolios had significant exposures to the ΔGEPU. Second, although the adjusted R^2 and average standard error of intercepts are the same in FF5 and its augmented version for OP portfolios, other metrics yield inferior results for augmented FF5. Average absolute intercepts were one basis point higher. This is not an economically significant effect. Therefore, it could be concluded that the model performs qualitatively similarly to the benchmark model. Including $\Delta GEPU_t$, only improves the performance of the FF5 in investment portfolios. Although the effects are economically insignificant (for instance, absolute intercept only decreased by one basis point), all the metrics imply that including the $\Delta GEPU_t$ factor improves the pricing performance of the FF5 in investment sorted portfolios.

[12] One basis point for average alphas and three basis points for the dispersion metric.

Table 8: The table presents the performance metrics of FF5 and the augmented version in explaining the test assets

Models	GRS	$A.\lvert\alpha_i\rvert$	$A.s(\alpha_i)$	$\frac{A.\lvert\alpha_i\rvert}{A.\lvert r_i\rvert}$	$\frac{A.\alpha_i^2}{A.r_i^2}$	$\frac{A.s^2(\alpha_i)}{A.\alpha_i^2}$	AR²
B/M Portfolios							
FF5 Augmented	32.97*	0.22	0.06	0.71	0.50	0.05	0.98
OP Portfolios							
FF5 Augmented	28.53*	0.17	0.05	0.87	0.75	0.06	0.99
Inv Portfolios							
FF5 Augmented	23.87*	0.16	0.05	0.70	0.48	0.06	0.99

Note. The sample covers the period from January 1997 to May 2023. Symbols ** and * represent statistical significance at 5% and 1% respectively.

Dispersion ratios for both models are less than 1, implying the models can deflate excess returns. In B/M sorts, the augmented model produces similar results to the benchmark model; however, in OP and investment sorts, the results are controverting. In investment-sorted portfolios, the augmented model outperforms the benchmark model by 0.06. In OP sorts, the augmented version produces a dispersion metric that is 8 basis points higher.

6. Robustness

We adopt three other measures to check if our results are robust to the alternative measures of policy uncertainty. First, following Petkova (2006), we use innovations in GEPU rather than the first difference since it can be argued that surprises in the policy uncertainty is a risk factor that requires a premium. GARCH(1,1) model is used to derive the innovations of the GEPU index; then, these innovations are used in the regression stated in **Equation 1** instead of $\Delta GEPU_t$. Second, as like Zaremba et al. (2022), we use $\Delta GEPU2 = \frac{GEPU_{t-1} - GEPU_{t-2}}{\sigma_{t-24}}$ as an alternative measure for economic uncertainty in our regressions. Third, instead of ΔGEPU, we use the first difference of the global geopolitical risk index (henceforth ΔGGPRt) of Caldara and Iacoviello (2022).[13]

We present the results for the robustness tests in **Table 9**. Considering the portfolios' exposures to our new proxies, in the regressions of B/M sorted portfolios, all the proxies are statistically insignificant at a 5% significance level. GARCH innovations are found to be significant only in two investment-sorted portfolios: big-aggressive and big-neutral portfolios.

For B/M portfolios, the choice of the policy uncertainty index does not affect the performance metrics. None of the models outperforms the benchmark model or the augmented FF5. In addition, when ΔGEPU2 was used as a regressor, the model produce an average absolute intercept of 1 basis point higher than the benchmark models. In contrast, for OP-sorted portfolios, the use of ΔGEPU2 and ΔGGPR improves the model's performance. When ΔGEPU2 is used instead of ΔGEPU, absolute average intercepts fell by two basis points, and when ΔGPR is used, one basis point reduction was observed in average absolute intercepts. Models yield these reductions with qualitatively similar average standard errors. Considering Investment sorted portfolios, using GARCH innovations or ΔGGPR does not improve the FF5 or its augmented version. Although using ΔGEPU2 improves intercepts, this was achieved with higher standard errors. The model produced 0.02 lower intercepts than the benchmark model, with a 0.09 increase in average standard errors.

[13] See https://www.policyuncertainty.com/gpr.html.

Table 9. The table presents the performance metrics of five models.

Models	GRS	$A.\lvert\alpha_i\rvert$	$A.s(\alpha_i)$	$\frac{A.\lvert\alpha_i\rvert}{A.\lvert r_i\rvert}$	$\frac{A.\alpha_i^2}{A.r_i^2}$	$\frac{A.s^2(\alpha_i)}{A.\alpha_i^2}$	AR^2
B/M Portfolios							
FF5 + GEPU2	32.88*	0.23	0.06	0.76	0.58	0.04	0.98
FF5 + Innov	32.76*	0.22	0.06	0.71	0.51	0.04	0.98
FF5 + GPR	32.74*	0.22	0.06	0.71	0.50	0.05	0.98
OP Portfolios							
FF5 + GEPU2	28.55*	0.14	0.05	0.71	0.50	0.07	0.99
FF5 + Innov	28.53*	0.16	0.05	0.80	0.64	0.06	0.99
FF5 + GPR	28.52*	0.15	0.05	0.79	0.63	0.06	0.99
Inv Portfolios							
FF5 + GEPU2	23.85*	0.15	0.14	0.69	0.47	0.47	0.99
FF5 + Innov	23.84*	0.17	0.05	0.76	0.57	0.06	0.99
FF5 + GPR	23.84*	0.17	0.05	0.75	0.57	0.06	0.99

Note. The models are the FF5 and augmented versions of the model. Augmented versions include one additional variable to the FF5 to proxy global policy uncertainity. GEPU2 stands for ΔGEPU2 = $GEPU_{t\text{-}1}$ - $GEPU_{t\text{-}2}/\sigma_{t\text{-}24}$, Innov is the innovations of GEPU index derived from a GARCH (1,1) model, and GPR is the first difference of Caldara and Iacoviello's (2022) geo-political risk index. Symbols ** and * represent statistical significance at 5% and 10% respectively. The sample covers the period from January 1997 to May 2023. Symbols ** and * represent statistical significance at 5% and 1% respectively.

7. Conclusions

In this article, we aimed to answer three main questions. First, whether the size, profitability, investment, and value anomalies documented mainly in developed equity markets were evident in the emerging markets. Second, whether FF5 can explain the cross-section of returns related to these anomalies in emerging markets. Third, whether the inclusion of GEPU into FF5 can improve the pricing ability of FF5 or whether there is a risk factor related to policy uncertainty that FF5 cannot capture.

Regarding the investigated anomalies, we find that the size effect is not pronounced in high B/M and aggressive investing stocks, whereas FF (2015) had a similar finding. Considering OP, B/M, and Investment effects, once the average portfolios are calculated following Ajili (2002), the anomalies are observed. However, in 2x3 sorted portfolios, anomalies are observed other than small OP sorted portfolios. This group do not yield an apparent profitability effect since neutral profitability portfolios earned higher average excess returns than high profitability portfolios.

Second, we find significant GRS tests for all test portfolios for CAPM, FF3, and FF5, implying all the models leave unexplained returns. Nevertheless, FF5 improves FF3 by leaving smaller absolute average intercepts in size-op and size-investment sorted portfolios. In B/M sorted portfolios, we find the absolute average intercepts were 0.22 for both FF3 and FF5, leading us to conclude for profitability and investment-related anomalies, RMW and CMA have no explanatory power. For B/M-related anomalies, FF3 is a more parsimonious model to explain the cross-section of returns.

After the inclusion of the global economic policy uncertainty index, we find that the explanatory power of FF5 does not improve. GRS tests remain significant, and average absolute intercepts do not economically enhance significantly. There was only one basis point of improvement in size-investment sorted portfolios. These results are find to be robust to the choice of index and the way of calculation. Overall, our findings suggest that for the sample investigated in this article, FF5 leaves unexplained excess returns, and the

Fama-French factors subsume risks associated with policy uncertainty and geopolitical risk.

The significance of our findings has implications that are of relevance to fund managers and investors in multiple aspects. Emerging markets exhibit various anomalies related to size, value, profitability, and investment. Consequently, implementing strategies that capitalise on these anomalies would likely result in superior returns for managers. Nevertheless, it is crucial for fund managers and investors to acknowledge that the five-factor model fails to account for certain unexplained returns when constructing portfolios or evaluating the performance of a portfolio manager. Investors who are considering investments in emerging markets should exercise caution when utilising the model. The alphas produced by a portfolio may be attributed to non-diversifiable risk factors that are not accounted for in the model. Furthermore, it is important for investors who are considering investments in emerging markets to recognise that the existing model is not complete. Consequently, attempting to estimate the cost of equity using this model would result in the omission of unpriced undiversifiable risk factors, ultimately leading to an underestimation of the cost of equity. Fund managers, on the other hand, should exercise caution when formulating their diversification strategy in light of our findings. While the model demonstrates an ability to account for the risk linked to global economic policy uncertainty, it falls short in comprehensively explaining all the returns. This suggests that the model overlooks systematic risk factors that are pertinent to emerging markets.

Our emerging markets data was pooled and treated as a single market while forming the factors and portfolios. It could be argued that the equity markets of emerging markets do not exhibit sufficient integration due to market frictions such as the free flow of capital between countries. This study could be further improved by developing factors and indices specific to each country and conducting tests to examine the hypothesis of a zero-intercept. Furthermore, Mosoeu and Kodongo (2022) showed that the performance of the FF5 can be sensitive to how the factors are constructed. Thus, future studies may consider testing the models by forming the factors with different procedures. Further, size factor (SMB) can be constructed by considering market specific characteristics following the suggestions of Ahn et al. (2019) and Hou and van Dijk (2019).

Author Contributions: Conceptualization, O.A., and A.A.; methodology, O.A.; software, O.A.; validation, O.A. and A.A.; formal analysis, O.A.; investigation, O.A.; data curation, A.A.; writing—original draft preparation, O.A.; writing—review and editing, A.A.; visualization, O.A. and A.A.; supervision, A.A.; project administration, O.A. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Data Availability Statement: Data can be gathered from: https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html.

Conflicts of Interest: Authors declare there are no conflict of interest or competing interests to declare.

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