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EMERGING MARKETS AND THE CONDITIONAL CAPM

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Emerging Market equity returns have proved challenging to model using conventional statistical tools. In this paper we use the conditional capital asset pricing model (CCAPM) together with an explicit expectations structure to arrive at a framework which can be easily estimated. We take the perspective that US equity corresponds to the market and that our investors are US dollar investors and use this approach to explain emerging market country index equity returns. Different choices of US equity index provide, unsurprisingly, different results. A noteworthy finding is that the Russell 2000 seems a better explanatory variable than the Russell 1000 suggesting that it is the small to medium capitalised US companies that help us understand emerging market returns.

Emerging Markets and the Conditional CAPM

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Abstract

Emerging Market equity returns have proved challenging to model using conventional statistical tools. In this paper we use the conditional capital asset pricing model (CCAPM) together with an explicit expectations structure to arrive at a framework which can be easily estimated. We take the perspective that US equity corresponds to the market and that our investors are US dollar investors and use this approach to explain emerging market country index equity returns. Different choices of US equity index provide, unsurprisingly, different results. A noteworthy finding is that the Russell 2000 seems a better explanatory variable than the Russell 1000 suggesting that it is the small to medium capitalised US companies that help us understand emerging market returns

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1. Introduction.

Emerging market equities have historically proven to be difficult to model through conventional asset pricing models such as the CAPM; see Sandoval and Saens (2004) and Hakim and Mohamad (2016) who survey the relevant literature. We attempt to model emerging market equities using the conditional CAPM. Our setting considers the perspective of a US investor looking to invest in emerging market indices. We do not address asset allocation decisions or cross-asset investments although our analysis can be used in these contexts. Rather, we consider how different EM indices are exposed to US market risk. Given the evolving nature of EM economies and other global factors, we need a framework that allows for non-constancy of risk exposure; such a framework is provided by the conditional CAPM.

Rabindranath et al (2019) provide a framework for estimating the conditional CAPM of Jagannathan and Wang, (1996) (CCAPM) which we apply to estimate a CCAPM structure for EM indices. We differ, trivially from Jagannathan and Wang, (1996) in specifying the CCAPM in terms of excess returns to cash rather than employing a zero-beta specification. We refer to our approach as the Conditional Sharpe-Lintner CAPM (SL-CCAPM) which we abbreviate to CCAPM. Note, that Rabindranath (ibid) propose a variety of different specifications that can be estimated empirically. We use their proposed market-timing model; however, the methodology introduced will be applicable to other models and specifications.

We define $E_t(X_{t+1})$ to mean the expectation of X_{t+1} given all information known at time t. The conditional SL-CCAPM is identical to the unconditional SL-CCAPM except that it will change as the conditioning information changes, thus it is the natural vehicle for discussing a changing beta. The conditional CAPM relationship becomes (see Jagannathan and Wang 1996):

$$E_t(R_{i,t+1})=E_t(R_{m,t+1})B_{i,t}$$

where $R_{i,t+1}$ is the excess return on asset i in period $t+1$ and $R_{m,t+1}$ is the excess return on the market portfolio in period $t+1$. $E_t(R_{m,t+1})$ can be interpreted as the conditional equity risk premium. The term $B_{i,t}$ is equal to $Cov_t(R_{i,t+1}, R_{m,t+1})/Var_t(R_{m,t+1})$ where Cov_t and Var_t are covariance and variance conditional upon all information known at time t (traditionally called the asset beta).

Jagannathan and Wang (1996) go on to show that if we take unconditional expectations of the conditional CAPM and use the Law of iterated expectations, we arrive at (see their equation 4):

$$E(R_{i,t+1}) = E\left(E_t(R_{m,t+1})\right) E(B_{i,t}) + Cov\left(B_{i,t}, E_t(R_{m,t+1})\right)$$

The first part of the relationship is, essentially the unconditional SL-CAPM taken at the average conditional equity risk premium and the average beta. The last term measures the covariance between the conditional beta and the conditional expected risk premium and is called the beta premium. The intuition behind this last term can be seen if we consider periods when we expect the equity risk premium to be high. In such periods of high risk, we might expect highly geared stocks to become even more geared so that, for such stocks, conditional beta moves with the expected equity risk premium and the beta premium is positive. This might be seen as a description of growth–orientated economies.

The beta premium sensitivity on the other hand is described as:

$$\psi_i \quad = \frac{Cov\left(B_{i,t}, E_t(R_{m,t+1})\right)}{Var\left(E_t(R_{m,t+1})\right)}$$

Jagannathan and Wang define the beta premium sensitivity as a 'measure of the sensitivity of the conditional beta to the market risk premium.' Thus, in our setting a higher beta-premium sensitivity will imply greater integration between the particular emerging market and the US financial market. The beta premium and the beta-premium sensitivity, hold out the promise of helping us classify emerging markets, so it may be thought that Asian versus Latin American markets, for example, might have different signs or different magnitudes for such measures.

Understanding when the beta premium is zero seems of some importance because it is those situations when the SL-CAPM will be valid taken at average values. Before we answer this question, we note that a simple requirement for the conditional CAPM to be valid is that the joint distribution of asset returns is conditional multivariate normal. By validity, we mean myopic validity. As is well known, conditional multivariate normality allows for specifications that are unconditionally non-normal. Requiring that the conditional CAPM be valid in a multi-period context requires stronger conditions as mentioned by Leroy (2000).

The efficacy of the conditional CAPM has been a source of some debate in Finance. While Jagannathan and Wang (1996) claim that the conditional CAPM is able to explain anomalies in asset returns, there are some notable detractors. Lewellen and Nagel (2006), highlight the failure of the conditional CAPM in explaining pricing anomalies. They do so by showing that the alpha (mis-pricing) as implied by short-window regressions on a mixture of portfolio returns, is significantly different from zero. As opposed to previous studies which tout the success of the conditional CAPM in explaining pricing anomalies, this article provides a test to evaluate the conditional CAPM.

Importantly, they highlight that the unconditional alpha depends on the covariance between the betas and the expected market risk premium (what we refer to as the beta premium) and the covariance between the betas and the volatility of market return. For plausible values of these quantities, they show that a sufficiently large unconditional alpha cannot be obtained and use this result to argue against the conditional CAPM. It must be noted that they do not attempt to derive analytical formulae for the unconditional alpha or the beta premium. We work with a specific model that gives us a closed form, empirically testable beta-premium term.

Campbell and Vuolteenaho (2004) break down an asset's beta into a good – discount rate beta and a bad, cash flow based beta to explain the value and size puzzles. The Cash flow (bad) beta usually commands a higher risk-premium in their setting and they provide a methodology for estimating the two betas. The notion of time varying coefficients is not considered but is implied. A more recent study that also tries to explain the value and small stock puzzle is Guo et al (2017)'s Time-Varying Beta and the Value Premium; they use a nonlinear methodology to fit for an alpha and reiterate Lewellen et al's finding that the conditional CAPM does better than the unconditional version but is unable to fully explain the value premium.

Bali and Engle (2017) resurrect the conditional CAPM explanation using a variety of different beta specifications and use daily returns to show that conditional CAPM still has merit even when the unconditional version does not. They also control for co-skewness in their regression in addition to other variables such as firm size, book-to-market, past returns, liquidity, turnover and volatility some of which are considered in Lewellen and Nagel (2006).

The results we obtain for Emerging markets strongly suggest that countries with higher co-skewness with the US financial market tend to have higher beta-premium sensitivity. Our findings are in line with earlier studies that relate emerging market returns to measures of co-skewness.

Harvey and Siddique (2000), in a seminal article contend that conditional skewness is an important factor in explaining cross-sectional variation in asset returns. Investors who take on skewness risk expect to be compensated for it. They use this to explain the momentum effect often observed in asset returns. While our mechanism is different, our conditional CAPM regression is similar to the one derived in this article under a quadratic stochastic discount factor.

Harvey (2000) separately analyses factors that may explain expected returns in international markets, differentiating between emerging and developed markets. He examines 18 such risk factors for his sample of countries between 1988 and 1999 and finds skewness to be an important factor for emerging but not developed markets. Specifically, he contends that if an asset has high co-skewness, the asset will be more valuable and command a higher price (vice versa). Similar results are found in Harvey (2001) and Bekaert et al (2007).

We make four contributions in this article drawing from the conditional CAPM, co-skewness and Emerging Market literatures. First, by assuming that the market-timing model holds, we are able to derive analytical formulae for the conditional SL-CAPM. We can empirically estimate these quantities, which we refer to as the beta premium and beta-premium sensitivity respectively. While we use a particular specification, the methodology can be applied more generally to test whether the conditional SL-CAPM holds.

Secondly, we are able to compute beta premium sensitivities for a number of emerging market economies, which helps us in understanding why certain emerging markets are more attractive from the perspective of a US investor. By comparing the beta premium sensitivities using different US stock market indices, we note that EM betas are more sensitive for investors considering US medium-small capitalizations than with large capitalizations.

Thirdly, we are also able to conclude that emerging markets with high co-skewness with the US market command a higher beta premium than those that do not. Through limited dependent variable regressions, we are able to show that co-skewness is the most critical factor in determining beta premium sensitivity in an emerging market compared to other measures, including trade openness and foreign exchange volatility (hedging motive).

Finally, we break down our measure of co-skewness into co-skewness with local returns and a co-skewness element coming from the return of currency, thereby allowing us to identify the underlying force driving an emerging market index's co-skewness with the relevant US market. This is irrespective of our choice of the market index. The analytical breakdown of the dollar return into a local currency and currency return is presented in Section 2 and its application is presented in Section 5. Thus, our contributions to the various literatures are both methodological and empirical.

Section 2 below outlines our conditional SL-CAPM model. Section 3 describes our data and empirical methodology. Section 4 discuss empirical estimation results, Section 5 reports results from our linear probability model regression and Section 6 concludes.

2. The Model

As mentioned above, Rabindranath et al (2018) recommend a specific model that gives us closed form solutions for the beta premium, $Cov\left(B_{i,t}, E_{t(R_{m,t+1})}\right)$ and the beta-premium sensitivity defined as,

$$\psi_i \quad = \frac{Cov\left(B_{i,t}, E_t\left(R_{m,t+1}\right)\right)}{Var\left(E_t\left(R_{m,t+1}\right)\right)}$$

They advocate the market timing model where conditional beta is assumed linear in market return (this will also generalise to higher orders), i.e.

$$B_{i,t+1} = a_i + b_i R_{m,t+1} \qquad (1)$$

They assume that market returns are autoregressive

$$R_{m,t+1} = a_m + b_m R_{m,t} + \varepsilon_{m,t+1} \qquad (2)$$

where it is assumed that $\varepsilon_{m,t+1}$ $is\ iid(0, \sigma^2)$.

Then, $E_t\left(R_{m,t+1}\right) = a_m + b_m R_{m,t}$, and

$$Var\left(E_t\left(R_{m,t+1}\right)\right) = b_m{}^2 Var(R_{m,t}).$$

From (2), we see that

$$Var(R_{m,t+1}) = b_m{}^2 Var(R_{m,t}) + \sigma^2 = \frac{\sigma^2}{1-b_m^2}$$

$$Var\left(E_t\left(R_{m,t+1}\right)\right) = \frac{b_m^2\sigma^2}{1-b_m^2}.$$

Let i represent an emerging market index. Then:

$$Cov\left(B_{i,t}, E_t\left(R_{m,t+1}\right)\right) = Cov(a_i + b_i R_{m,t}, a_m + b_m R_{m,t}) = b_i b_m \frac{\sigma^2}{1-b_m^2}.$$

$$\psi_i \quad = \frac{b_i b_m \frac{\sigma^2}{1-b_m^2}}{b_m^2 \frac{\sigma^2}{1-b_m^2}}$$

$$\psi_i = b_i / b_m \qquad (3)$$

This result stands assuming that the conditional CAPM is valid; if we further assume that:

$$R_{i,t+1}=B_{i,t+1}R_{m,t+1}+\varepsilon_{i,t+1} \tag{4}$$

then, combining (1) and (4),

$$R_{i,t+1}=(a_i+b_iR_{m,t+1})R_{m,t+1}+\varepsilon_{i,t+1}\ , \tag{5}$$

which gives a quadratic market model. We can estimate (2) and (5) by ordinary least squares (OLS) to estimate ψ_i. A constant δ_i may be included if desired. We do include a constant in our OLS regression estimates but do not report them in our results as these are invariably insignificant.

We make a further justification for the Beta premium based on its connection with co-skewness; we define $\sigma_{i,2m}=Cov\left(R_{i,t+1},R_{m,t+1}^2\right)$ and using similar notation throughout we find that

$$\hat{b}_m=\frac{Cov\left(R_{m,t+1},R_{m,t}\right)}{\sigma_{m,m}}$$

$$\hat{b}_i=\frac{-\sigma_{m,2m}\sigma_{i,m}+\sigma_{m,m}\sigma_{i,2m}}{\sigma_{m,m},\sigma_{2m,2m}-\sigma_{m,2m}\sigma_{m,2m}} \tag{6}$$

$$\psi_i=\frac{-\sigma_{m,2m}\sigma_{i,m}+\sigma_{m,m}\sigma_{i,2m}}{\sigma_{m,m}\sigma_{2m,2m}-\sigma_{m,2m}\sigma_{m,2m}}\Big/\frac{Cov\left(R_{m,t+1},R_{m,t}\right)}{\sigma_{m,m}} \tag{7}$$

Note that the analytical expression for beta premium sensitivity will vary under different specifications. Rabindranath et al (2018) also consider GARCH and stochastic volatility specifications. In addition to deriving analytical expressions for the beta premium and the beta premium sensitivity, we also provide an empirical application in the context of emerging markets.

Notice that $\sigma_{i,2m}$ is closely related to co-skewness, which we define as:

$$CS_{i,m}=E\left[\left(R_{i,t+1}-E\left(R_{i,t+1}\right)\right)\left(R_{m,t+1}-E\left(R_{m,t+1}\right)\right)^2\right]$$

Indeed, $CS_{i,m}=\sigma_{i,2m}-2E\left(R_{m,t+1}\right)\sigma_{i,m}$ (8)

where $CS_{i,m}$ represents Co-skewness.

If we work with correlations and standardized variances instead, we get the following representation:

Define: $SCS_{i,m} = \frac{E\left[\left(R_{i,t+1}-E(R_{i,t+1})\right)\left(R_{m,t+1}-E(R_{m,t+1})\right)^2\right]}{\sigma_i \sigma_m^2}$; $\rho_{i,m} = \frac{\sigma_{i,m}}{\sigma_i \sigma_m}$;

$$\rho_{i,2m} = \frac{\sigma_{i,2m}}{\sigma_i \sigma_{2m}};\ SR(R_{m,t+1}) = \frac{E(R_{m,t+1})}{\sigma_m}$$

Then, $SCS_{i,m} = \frac{\sigma_{2m}}{\sigma_m^2}\rho_{i,2m} - SR(R_{m,t+1})\rho_{i,m}$

where $SCS_{i,m}$ is the standardized Co-skewness, $\rho_{i,m}$ is the correlation between an emerging market index and the market return; $\rho_{i,2m}$ is the correlation between an emerging market index and the quadratic market return and $SR(R_{m,t+1})$ is the Sharpe ratio of the market return.

We now turn to the contribution of currency in our calculations. We see that $R_{i,t+1} = R_{i,t+1}^l + FX_{i,t+1}$ where the first term is in the rate of return in local currency whilst the second term is the return on the exchange rate. We immediately have the following result:

Theorem 1:

The terms $\hat{b}_i = \frac{-\sigma_{m,2m}\sigma_{i,m}+\sigma_{m,m}\sigma_{i,2m}}{\sigma_{m,m},\sigma_{2m,2m}-\sigma_{m,2m}\sigma_{m,2m}}$; $\psi_i = \frac{\frac{-\sigma_{m,2m}\sigma_{i,m}+\sigma_{m,m}\sigma_{i,2m}}{\sigma_{m,m}\sigma_{2m,2m}-\sigma_{m,2m}\sigma_{m,2m}}}{\frac{Cov(R_{m,t+1},R_{m,t})}{\sigma_{m,m}}}$;

$CS_{i,m} = \sigma_{i,2m} - 2E(R_{m,t+1})\sigma_{i,m}$ *are all decomposable into two components, one for local returns and the other for currency.*

Proof:

Since $\sigma_{i,m} = Cov(R_{i,t+1}; R_{m,t+1}) = Cov(R_{i,t+1}^l; R_{m,t+1}) + Cov(FX_{i,t+1}; R_{m,t+1})$ and $\sigma_{i,2m} = Cov(R_{i,t+1}; R_{m,t+1}^2) = Cov(R_{i,t+1}^l; R_{m,t+1}^2) + Cov(FX_{i,t+1}; R_{m,t+1}^2)$, the result follows immediately.▫

In Section 5 we decompose $\sigma_{i,2m}$ into its local and FX components to understand the main driver for co-skewness for each emerging market index.

An alternate version of co-skewness as considered by Harvey and Siddiqui (2000) is:

$$\frac{E\left[\left(R_{i,t+1}-E(R_{i,t+1})\right)\left(R_{m,t+1}-E(R_{m,t+1})\right)^2\right]}{E\left(R_{m,t+1}-E(R_{m,t+1})\right)^3}$$

Our results and decompositions follow through as in Theorem 1. For consistency, we use this formula to calculate co-skewness. We choose this formula as it allows us to comment on the relative co-skewness across different indices by virtue of having the same denominator.

3. Data and Descriptive Statistics

Our emerging market data set comprises of all emerging market countries included in the Morgan Stanley Capital International (MSCI) Emerging Market Index, with the exception of China and Russia. We contend that it may be erroneous to assume that the Chinese and Russian economies are exogenous to US financial markets (which is implied under our methodology), thus, index returns from these two countries are not a part of our study.

Our data set, thus, includes weekly index returns from 22 emerging market economies, from January 2008 to June 2018. For some countries, the data start from June 2010. Where a choice of indices was available, we chose the index with the highest market capitalization. Since each market is being analysed from the perspective of a US investor, we converted each index return to a dollar denominated return by adding the return on the index and the return on the foreign currency vis a vis the dollar.

Unsurprisingly, given how strong the US dollar has been over the last decade with respect to most major currencies, a lot of emerging market indices, despite good performance otherwise had small dollar denominated returns. There is debate on whether emerging markets should continue to be treated as worthwhile investments or not. Wheatley, 2019 has a bearish view of emerging markets apart from China and India; he believes that political events coupled with a strong dollar and the Trump regime's economic policies may make emerging markets a less lucrative investment. Stevenson (2017) on the other hand adopts a bullish tone although his article predates the trade wars initiated since 2017. We have stated at the outset that our article's scope does not extend to considering asset allocation decisions and instead, we focus on whether our CCAPM is a better explanator of emerging market equity returns than the unconditional CAPM and if so, for which countries. Irrespective of how emerging market equities behave in the near future, if we can understand these movements better through our model, our contribution will have been significant.

All emerging market index and currency data were obtained from Investing.com. The US investor gains if the respective emerging market currency appreciates, thus, she gets more dollars per unit of foreign currency. Table 1 reports descriptive statistics for our data, disaggregating emerging market index return in dollars into an emerging market index return in local currency and a currency return.

For the choice of the market index, we could use a global measure but for ease of interpretation, we prefer to use a domestic US equity index; we consider the S&P500, the Russell 1000 and the

Russell 2000 indices. We find that the former two have more predictability in terms of (2) but the coverage is too narrow. The Russell 2000, in terms of (2) is not statistically significant but tends to correlate with more emerging markets (as in (1)). Since our interest is in emerging markets, we proceed with the Russell 2000 and use the Russell 1000 for comparative analysis. We do not report the S&P500 results, which are available upon request. Table 1 reports descriptive statistics for the market indices. The S&P500 results are somewhat similar to the Russell 1000 index results, but as mentioned above, since the Russell 1000 has broader coverage than the S&P500 we report these results instead of the S&P500 results.

We postulate that the Russell 2000 index is the more relevant market index for emerging markets as it covers Medium to Small Cap industries, which provide the relevant benchmark for emerging markets. The Russell 1000 on the other hand is a large cap index and may not be a relevant market return for emerging markets from the perspective of a US investor. The Russell 1000 index is an index of the 1000 largest companies in the US by market capitalization. The Russell 2000 on the other hand includes the next 2000 largest companies. There is no overlap in the two indices although as market capitalizations change, a company may move to the Russell 2000 from the Russell 1000 and vice versa. Together they form the Russell 3000 index, which aims to benchmark the US equity market. Our contention that the Russell 2000 is the most appropriate market index with regards to a conditional CAPM model considering emerging market indices is supported by some finance practitioners and financial analysts (see Stevensen, D. 2017).

All returns are excess returns where R_f is the 3-month US treasury rate; thus, these returns are from the perspective of the US investor. The return has been converted from annual to a weekly return. In order to calculate $R_{i,t}$, we have considered the US investor's return on the currency in addition to the return on the relevant stock market index. So, $R_{i,t+1} = R^l_{i,t+1} + FX_{i,t+1}$, where $R^l_{i,t+1}$ is the weekly return between periods t+1 and t in local currency and $FX_{i,t+1}$ is the weekly gain between t+1 and t on the country's currency vis a vis the US dollar i.e. how many more dollars 1 unit of the local currency can buy.

Table 1 shows annualised average returns for each index, annualised average returns on the domestic currency vis a vis the dollar, the annualised average total return, annualised volatilities for the respective indices and currencies and the correlation between the weekly return and the currency return. Note, that the annualised average total return does not simply equal the sum of annualised average index return and the annualised average currency return since we compound each return after averaging (instead of averaging annualised weekly returns).

We note that the US indices, the Russell 2000 in particular, outperformed most emerging market indices even if we consider each index return in domestic currency. Over the 10 years under consideration, the Russell 2000 achieved a return of 11.45% with annualised volatility of 23.11%. Only Hungary, Pakistan, Philippines and Thailand were able to outperform all the US indices considered in the study. The Philippine index achieved a return of 14.58% with a relatively low volatility of 15.74% followed by the Pakistani and Thai index returns. This may explain Wheatley's (2019) bearish view of emerging market equities mentioned above.

However, when converted to dollars, only the Philippines and Thai indices outperform US indices. This is evident from the appreciation of the US dollar over the period under consideration. The only currencies that gained against the year US dollar over this period were the Thai Bath and the Taiwanese dollar. The Qatari Riyal and UAE Dirham are pegged against the dollar and show little to no movement. Thus, from the perspective of the US investor, the Russell 2000 would have yielded better returns than emerging markets; however, some of the emerging markets offer lower return volatility making them more attractive to a risk-averse investor. It is interesting to note that some emerging market that are given a significant amount of coverage in the US media, such as Brazil, India and Mexico achieved low and in the case of Brazil and Mexico negative average annualised returns over the ten-year period. We do not notice any pattern in the correlation between index returns and currency returns. We consider whether this correlation is a determining factor in the conditional CAPM being the relevant model for an emerging economy in Section 5.

Table 1 – Descriptive Statistics (Annualized)

Country/Index	Currency	$R^l_{i,t+1}$	$FX_{i,t+1}$	$R_{i,t+1}$[1]	$s_{R^l_{i,t+1}}$	$s_{FX_{i,t+1}}$	$s_{R_{i,t+1}}$	$\rho_{l,FX}$
Russell 1000	USD	8.83%	NA	8.83%	19.53%	NA	19.53%	NA
Russell 2000	USD	11.45%	NA	11.45%	23.11%	NA	23.11%	NA
S&P500	USD	8.45%	NA	8.45%	18.17%	NA	18.17%	NA
US-3 Month	USD	0.37%	NA	0.37%	0.08%	NA	0.08%	NA
Brazil	BRL	5.77%	-8.14%	-2.84%	25.82%	16.09%	38.13%	0.64
Chile	CLP	8.70%	-3.37%	5.04%	15.08%	12.42%	22.92%	0.38
Colombia	COP	6.46%	-4.38%	1.80%	17.06%	13.64%	25.34%	0.37
Czech Rep.	CZK	-1.55%	-2.91%	-4.42%	22.34%	12.92%	28.26%	0.23
Egypt	EGP	8.95%	-12.56%	-4.71%	30.59%	24.53%	37.15%	-0.10
Greece	EUR	-4.08%	-0.55%	-4.89%	33.71%	9.24%	35.55%	0.07
Hungary	HUF	12.62%	-4.20%	7.90%	19.75%	13.71%	28.22%	0.40
India	INR	7.64%	-5.30%	1.94%	21.30%	7.82%	23.66%	0.13
Indonesia	IDR	9.85%	-3.96%	5.51%	20.69%	7.90%	25.56%	0.50
Korea	KRW	5.05%	-1.95%	3.00%	19.22%	11.50%	28.02%	0.64
Malaysia	MYR	6.91%	-1.74%	5.06%	9.50%	7.63%	14.99%	0.00
Mexico	MXN	6.75%	-6.51%	-0.19%	20.25%	12.73%	29.11%	0.53
Pakistan	PKR	14.08%	-5.81%	7.47%	20.57%	4.84%	21.38%	0.00
Peru	PEN	6.06%	-1.20%	4.81%	26.08%	5.13%	28.27%	-0.34
Philippines	PHP	14.58%	-1.43%	12.95%	15.74%	5.47%	18.42%	0.36
Poland	PLN	9.44%	-2.27%	6.96%	16.08%	13.03%	24.62%	0.42
Qatar	QAR	2.47%	0.00%	2.47%	23.72%	1.18%	23.83%	-0.06
South Africa	ZAR	9.25%	-7.56%	1.01%	18.36%	17.58%	29.85%	0.38
Taiwan	TWD	4.86%	0.69%	5.58%	18.02%	4.73%	20.59%	0.45
Thailand	THB	12.70%	0.62%	13.40%	16.56%	4.69%	19.11%	0.44
Turkey	TRY	9.76%	-13.03%	-4.52%	26.19%	13.74%	36.22%	0.61
UAE	AED	-2.68%	0.00%	-2.68%	27.55%	0.09%	27.55%	-0.03

**$R^l_{i,t+1}$ – Average Annualised index return in domestic currency; $FX_{i,t+1}$ – Average Annualised Change in domestic currency vs USD; $R_{i,t}$ – Aaverage Annualised Index return in USD; $s_{R^l_{i,t+1}}$- Annualised index volatility in domestic currency; $s_{FX_{i,t+1}}$- Annualised currency volatility vs USD; $s_{R_{i,t}}$ – Annualised index volatility in USD; $\rho_{l,FX}$ – correlation between index return in domestic currency and return on domestic currency vs USD*

[1] $R_{i,t+1} \neq R^l_{i,t+1} + FX_{i,t+1}$ due to the impact of annual compounding.

4. Conditional CAPM Regression Results

We empirically estimate equation (5) for all emerging market indices using the Russell 2000 and Russell 1000 indices as market returns respectively. In order to compute the beta-premium sensitivity, we also need to estimate equation (2). OLS results for equation (2) are reported in Table 2 below. As indicated in Section 2, only the Russell 1000 has predictability in terms of equation (2) (i.e. has statistically significant coefficients). Because the S&P500 index does not have sufficient coverage for this analysis, we proceed with the Russell 1000 and Russell 2000 indices.

Table 2 – Results for an AR(1) on Market return

Index	a_m $SE(a_m)$	b_m $SE(b_m)$
Russell 1000	0.0019* (0.0011)	-0.151*** (0.042)
Russell 2000	0.0022 (0.0014)	-0.046 (0.043)
S&P 500	0.0017 (0.0011)	-0.082* (0.043)

* statistical significance at 10%; **statistical significance at 5%; ***statistical significance at 1%

Tables 3 and 4 report our regression results along with standard errors[2], distinguishing between countries that do and do not follow the conditional CAPM model as set out by the criterion in Section 2 (i.e. b_i is statistically significant). We only report coefficients of interests i.e. a_i, b_i and ψ_i. Full regression results are available upon request. Statistical significance is highlighted only for b_i as a_i was statistically significant for all countries at the 10% level and for most at the 1% level.

When we use the Russell 2000 as the market index, we note that 17 out of the 22 countries in our sample, appear to follow the conditional version of the SL-CAPM and for the remainder, the unconditional version holds. With the Russell 1000 on the other hand, the number of countries that follow the conditional CAPM reduces to 12. This only indicates that the relevance of the conditional SL-CAPM when applied to emerging market indices depends on the underlying market return in question. Most switches occur from the conditional to the unconditional version as an additional 5 countries now follow the unconditional as opposed to the conditional version. Turkey is the only outlier as it follows the conditional CAPM when

[2] Results with Robust Standard Errors (not reported) are slightly different and some countries do not follow the conditional CAPM as a result; however, the changes are not significant enough to undermine our findings and are thus not reported.

compared against the Russell 1000 and the unconditional CAPM when the relevant market return is the Russell 2000. Thus, the results for the unconditional version seem robust.

The determinants of this classification are not clear on the surface. It is difficult to say without additional data, whether the conditional CAPM holds for countries that have better geographical linkages with the US (such as Latin American countries), are more developed, are better performing (such as the Philippines or Thailand) or are more globally integrated. We analyse these determinants in the next section.

A striking feature to note from Tables 3 and 4 however, is the role played by the beta sensitivity. Countries for which the conditional CAPM holds have much higher beta sensitivity on average. For instance, with the Russell 2000 as the relevant market index, countries in Table 3A have an average market beta sensitivity of 44.02 as opposed to just 4.86 for countries in Table 3B. The pattern is repeated when we use the Russell 1000 as the market return. With respect to the Russell 1000, average beta premium sensitivity is 13.86 for countries in Table 4A (conditional CAPM is valid) and 4.17 for countries in Table 4B (conditional CAPM not valid). We also note that countries carrying a beta-premium also have higher beta sensitivities. All countries in table 3A and 4A have higher beta sensitivities than countries in tables 3B and 4B respectively.

Another important feature of our results is that beta premium sensitivity is much higher when we consider the Russell 2000 index as opposed to the Russell 1000 index as our market return. As previously mentioned, we believe that the Russell 2000 is the more relevant index when evaluating an emerging market index as an emerging market index would provide better diversity against small and medium cap US stocks. Thus, it is indicative of a higher substitutability between US small, medium cap stocks, and emerging market indices. Emerging market indices do not appear to be as important to the large cap US investor if we consider the beta premium sensitivity as a measure of importance.

Our empirical methodology provides a useful test for analysing different emerging markets from the perspective of different investors (whether based in the United States or locally). After testing whether the conditional or unconditional SL-CAPM is the more applicable model for an emerging market, mispricing and different equity market puzzles can be evaluated in the correct context. We abstain from discussing investment profitability in the current article and focus instead on the applicability of the conditional CAPM model on emerging market equities. What this also highlights, is that the applicability of the right model is dependent on the investor's perspective. Countries that appear to follow the conditional CAPM may not do so from the perspective of say a European investor. The methodology applied in this section, however, will allow any investor to classify an emerging market appropriately and to apply the correct version of the CAPM subsequently.

In the next section, we try to identify the factors that determine whether an emerging market follows the conditional version of the CAPM, which in the context of this article is equivalent to the existence, or nonexistence of a beta premium.

Table 3A – Regression Results for Conditional CAPM – countries where it holds (RUS2000)

Country	a_i $SE(a_i)$	b_i $SE(b_i)$	$\psi_i = b_i/b_m$
Brazil	1.07 (0.05)	-1.39** (0.69)	30.15
Chile	0.52 (0.03)	-2.78*** (0.45)	60.30
Colombia	0.57 (0.04)	-1.33*** (0.51)	28.85
Czech Republic	0.77 (0.04)	-1.02** (0.52)	22.34
Egypt	0.36 (0.07)	-2.02** (0.86)	43.82
Greece	0.76 (0.09)	-4.10** (1.80)	88.50
Hungary	0.69 (0.06)	-2.32* (1.19)	50.33
India	0.51 (0.04)	-2.00*** (0.48)	43.38
Indonesia	0.47 (0.04)	-2.86*** (0.54)	62.04
Korea	0.78 (0.04)	-1.21** (0.51)	26.25
Mexico	0.91 (0.04)	-0.84* (0.48)	18.22
Peru	0.50 (0.04)	-1.42*** (0.51)	30.80
Philippines	0.38 (0.04)	-2.33*** (0.80)	50.54
Poland	0.71 (0.05)	-2.56*** (0.97)	55.53
Qatar	0.21 (0.04)	-2.32*** (0.54)	50.33
Taiwan	0.47 (0.03)	-0.93** (0.42)	20.17
UAE	0.20 (0.06)	-3.08*** (1.03)	66.81

* statistical significance at 10%; **statistical significance at 5%; ***statistical significance at 1%

Table 3B – Regression Results for Conditional CAPM – countries where it does not hold

Country	a_i $SE(a_i)$	b_i $SE(b_i)$	$\psi_i = b_i/b_m$
Malaysia	0.33 (0.03)	-0.68 (0.65)	14.75
Pakistan	0.07 (0.04)	-0.36 (0.51)	7.81
South Africa	0.90 (0.04)	0.00 (0.51)	0.00
Thailand	0.44 (0.04)	0.44 (0.82)	-9.33
Turkey	0.87 (0.06)	-0.51 (0.72)	11.06

Table 4A – Regression Results for Conditional CAPM – countries where it holds (RUS1000)

Country	a_i $SE(a_i)$	b_i $SE(b_i)$	$\psi_i = b_i/b_m$
Chile	0.40 (0.05)	-1.75*** (0.63)	11.67
Egypt	0.14 (0.08)	-2.49** (1.09)	16.67
Greece	0.62 (0.12)	-4.21** (1.81)	28.07
India	0.43 (0.05)	-1.83*** (0.65)	12.20
Indonesia	0.30 (0.05)	-3.12*** (0.72)	20.80
Korea	0.68 (0.05)	-1.34* (0.72)	8.93
Peru	0.40 (0.05)	-2.08*** (0.69)	13.87
Poland	0.65 (0.07)	-1.90* (1.13)	12.67
Qatar	0.16 (0.05)	-1.60** (0.69)	10.73
Taiwan	0.42 (0.04)	-1.29** (0.56)	8.67
Turkey	0.72 (0.07)	-1.64* (0.98)	10.93
UAE	0.11 (0.06)	-1.67** (0.81)	11.13

* statistical significance at 10%; **statistical significance at 5%; ***statistical significance at 1%

Table 4B – Regression Results for Conditional CAPM – countries where it does not hold

Country	a_i $SE(a_i)$	b_i $SE(b_i)$	$\psi_i = b_i/b_m$
Brazil	0.91 (0.07)	-0.69 (1.00)	4.67
Colombia	0.55 (0.05)	-0.81 (0.68)	5.40
Czech Republic	0.61 (0.06)	-0.66 (0.76)	4.40
Hungary	0.62 (0.07)	-1.12 (1.35)	7.53
Malaysia	0.30 (0.04)	-0.59 (0.73)	3.93
Mexico	0.80 (0.05)	-0.15 (0.72)	1.00
Pakistan	0.07 (0.05)	-0.43 (0.63)	2.87
Philippines	0.34 (0.05)	-0.59 (0.89)	3.93
South Africa	0.82 (0.06)	-0.24 (0.74)	1.60
Thailand	0.38 (0.05)	-0.96 (0.92)	6.40

5. Determinants of a beta premium

Once we have identified emerging markets with a beta premium (conditional CAPM holds), we analyse some of the characteristics of these countries through a limited dependant variable regression. We use the linear probability model to do this instead of a Logit or Probit regression as the returns under consideration (emerging market economies) do not appear to be generated as either a logistic or a normal distribution. Countries with a beta premium are given a value of 1 and those without a beta premium a value of 0 for the purposes of this analysis.

We consider a variety of different factors that could potentially indicate whether an emerging market may follow the conditional version of CAPM. Some of these factors were highlighted earlier and include average GDP growth over the ten-year period, institutional and legal infrastructure, global connectivity as measured through trade openness and the correlation between index return and currency return over the 10-year period.

In addition to these economic factors, Section 2 suggests some statistical factors. The analytical formula for beta sensitivity suggests that co-skewness is an important factor in determining its magnitude. Our results in Section 4 also suggest that beta premium sensitivity is higher for countries that follow the conditional version of CAPM. Thus, we incorporate co-skewness as an additional factor; this is in line with Harvey (2000) who highlights the importance of co-skewness in the emerging market context.

Data for GDP growth and Trade Openness were obtained from the World Bank's World Development Indicators (WDI) database. For data on legal and institutional infrastructure, we relied on the World Bank's Worldwide Governance Indicators project, which provides governance related measures on six dimensions. These include Voice and Accountability, Political Stability, Government Effectiveness, Regulatory Quality, Rule of Law and Control of Corruption – factors that could encourage foreign investment in a country albeit to varying degrees. We combine the different measures into a single, equally weighted index, based on the rankings obtained by different countries and refer to it as WGI or the World Governance Index.

Unsurprisingly the more developed a country, the higher it ranks on the WGI scale. Thus, it offers a better and more comprehensive measure of a country's development than a simple GDP based measure. Chile, the Czech Republic and Taiwan have the highest rank on the WGI scale whereas Pakistan, Egypt and Indonesia rank the lowest. Qatar and UAE, perhaps the richest countries in the sample, rank in the middle due to their poor record with regards to the

Accountability indicator. Table 5 reports the normalised WGI score (highest rank = 100), Average GDP growth in percentage terms, Average openness (Trade as a percentage of GDP), the correlation between the country's index return and its currency against the US dollar and the Co-skewness.

Table 5 – Conditional CAPM factors

Country	WGI	GDP growth %	Openness	ρ	Co-skewness w/ RUS2000	Co-skewness w/RUS1000
Brazil	62	1.59	24.62	0.636	2.515	1.663
Chile	100	3.01	65.71	0.383	3.413	2.299
Colombia	53	3.61	37.11	0.370	1.954	1.358
Czech Rep.	96	1.56	141.92	0.230	1.838	1.325
Egypt	33	3.90	44.97	-0.105	2.480	2.870
Greece	75	-2.82	60.28	0.069	1.240	3.166
Hungary	86	1.08	164.10	0.403	0.889	1.464
India	53	7.05	48.78	0.135	2.582	2.413
Indonesia	48	5.46	46.62	0.497	3.437	3.675
Korea	89	3.10	94.62	0.641	2.062	2.136
Malaysia	73	4.74	147.91	0.000	0.308	0.720
Mexico	54	2.07	65.74	0.534	1.780	0.965
Pakistan	25	3.74	30.93	0.001	0.448	0.538
Peru	54	4.90	50.06	-0.337	2.380	2.895
Philippines	49	5.61	66.76	0.357	0.825	0.793
Poland	92	3.37	89.98	0.424	0.970	1.836
Qatar	83	8.30	93.31	-0.064	2.630	1.893
SouthAfrica	72	1.77	61.45	0.379	0.897	1.076
Taiwan	97	2.70	122.70	0.450	1.434	1.816
Thailand	52	3.05	130.12	0.442	0.006	1.019
Turkey	58	5.09	49.86	0.608	1.407	2.496
UAE	82	2.93	161.86	-0.030	3.400	1.923

In table 6 we report our linear probability model results. To test for robustness of our results we run the regression using the classification as implied by the Russell 1000 index and include the co-skewness of emerging market returns with the Russell 1000 as the relevant control. Co-skewness is clearly the leading indicator of whether the conditional CAPM is relevant for a country. Countries that contribute to the skewness of the underlying market return are more attractive from the investor's perspective and thereby command a beta premium. Co-skewness is statistically significant for both set of results and the overall regression is also statistically significant.

Interestingly, regression results for the Russell 1000 index are more revealing and statistically significant. This highlights that, when considered against a large-cap market index, in addition to co-skewness, Institutional strength and GDP growth are also relevant factors. Both factors are less relevant when compared against small and mid-cap stocks. Thus, fast growing economies that have strong or strengthening institutions and that contribute to the skewness of US market returns, are the most likely candidates to have a beta premium and for such countries the conditional CAPM could be an appropriate model.

Table 6 – LPM Results w/Russell 2000 and Russell 1000

Conditional CAPM$_i$	*w/ Russell 2000*	*w/ Russell 1000*
WGI – normalised	0.0031	0.0084**
	(0.006)	(0.003)
Avg GDP Growth %	-0.0278	0.0598***
	(0.038)	(0.016)
Avg Openness	-0.0004	-0.0007
	(0.002)	(0.002)
Equity FX Correlation	-0.0952	-0.2380
	(0.315)	(0.2236)
Co-skewness	0.2579**	0.4596***
	(0.092)	(0.084)
Constant	0.2541	-0.9483***
	(0.338)	(0.287)
Std. Errors	Robust	Robust
R^2	0.4503	0.8016
F-Statistic	2.62*	23.70***

As noted in Section 2, the co-skewness measure in our context depends on two factors, a part contributed by the emerging market index return in local currency and a second part determined by currency return. In Table 7A, we break down part of the co-skewness measure into its local return and currency components for further analysis. Table 7B shows the contribution of the local return and currency elements of co-skewness in percentage terms.

At first glance, it is difficult to draw conclusions from this decomposition. There does not appear to be a clear pattern determining whether a country follows the conditional CAPM and whether most of its co-skewness is derived from co-skewness with local return or co-skewness with currency returns. Total co-skewness tends to matter but factors determining total co-skewness are idiosyncratic and country specific.

Upon deeper reflection, however, we note that countries which do not follow the conditional CAPM when using the Russell 2000 as the benchmark return (these include Malaysia, Pakistan, South Africa, Thailand and Turkey), tend to have a negative co-skewness component (Turkey being the exception here). South Africa and Thailand both have significant negative co-skewness being contributed from their local returns whereas Pakistan's FX co-skewness is negative. Malaysia's co-skewness contribution appears statistically and economically trivial compared to the other countries. The decomposition further allows us to understand, for each index, whether the main contributing factor to the portfolio's skewness is local currency returns or the return on currency in dollars.

Table 7A: Co-skewness decomposition (w/RUSSELL 2000)

Country	Co-skewness($)	Co-skewness(local)	Co-skewness(FX)
Brazil	2.515	1.078	1.438
Chile	3.413	1.916	1.497
Colombia	1.954	1.195	0.760
Czech Rep.	1.838	1.479	0.360
Egypt	2.480	2.395	0.087
Greece	1.240	1.303	-0.066
Hungary	0.889	0.514	0.377
India	2.583	1.691	0.892
Indonesia	3.437	2.233	1.204
Korea	2.062	1.048	0.165
Malaysia	0.308	0.145	0.214
Mexico	1.780	0.214	1.571
Pakistan	0.448	0.485	-0.037
Peru	2.383	2.182	0.201
Philippines	0.825	0.681	0.146
Poland	0.970	0.544	0.427
Qatar	2.630	2.635	-0.006
South Africa	0.897	-0.154	1.052
Taiwan	1.434	1.144	0.290
Thailand	0.006	-0.046	0.051
Turkey	1.407	0.717	0.691
UAE	3.400	3.401	-0.001

* *The statistical discrepancy between Total skewness in dollars and the sum of local currency co-skewness and FX co-skewness is due to the impact of the risk-free rate of return which is subtracted from the dollar return before co-skewness is calculated in dollars.*

Some specific findings are worth mentioning from the decomposition. As one would expect, Qatar and the UAE have 0 FX co-skewness as their currencies are pegged to the US dollar and over the period under consideration, this peg has been maintained. Thailand also warrants further comment. The large local and currency co-skewness values, as seen in table 7B, are due to the total co-skewness being a very small number (0.006). Local return co-skewness (-0.046) and currency co-skewness (0.051) negate each other. Looking beyond the magnitudes of total, local and currency co-skewness however, it is interesting to note that Thailand has had periods of economic turmoil in part due to local economic shocks and often due to political upheaval. The country has seen multiple coups over the past 10 years, which have led to large drops in the stock market, as reflected in the negative co-skewness of local returns. Thailand is only one of two countries in our sample (the other being Taiwan) that appreciated against the US dollar. Thailand follows a managed-float exchange rate regime and given increasing exports and international reserves, the currency has grown in value against the dollar. Strong growth in the Thai Baht is prominent from 2016-2018 with persistence noted in 2016 and 2017. Nevertheless, despite positive co-skewness, the currency has low volatility compared to the volatility of the SET 50 index in local currency.

Table 7B – Local and FX Contribution to Co-skewness (%)

Country	Co-skewness cont'b from domestic returns	Co-skewness cont'b from currency returns
Brazil	42.9%	57.1%
Chile	56.1%	43.9%
Colombia	61.1%	38.9%
Czech Rep.	80.5%	19.5%
Egypt	96.5%	3.5%
Greece	105.3%	-5.3%
Hungary	57.7%	42.3%
India	65.5%	34.5%
Indonesia	65.0%	35.0%
Korea	49.2%	50.8%
Malaysia	53.4%	46.6%
Mexico	12.0%	88.0%
Pakistan	108.3%	-8.3%
Peru	91.6%	8.4%
Philippines	82.4%	17.6%
Poland	56.0%	44.0%
Qatar	100.2%	-0.23%
South Africa	-17.2%	117.2%
Taiwan	79.8%	20.2%
Thailand*	-890.4%	990.4%
Turkey	50.9%	49.1%
UAE	100.0%	0.0%

**Total skewness for Thailand is close to 0. Negative local co-skewness is offset by positive currency co-skewness*

Next, we consider the portfolio of emerging market indices and calculate the co-skewness of the overall portfolio, first including and then excluding countries that do not follow the conditional CAPM. To weight this portfolio, we consider equal weights and GDP based weights. The equally weighted portfolio with all 22 countries included has a co-skewness of 1.78 with 1.21 contributed by returns from local currency. Contrast this with the GDP weighted portfolio, which has a higher co-skewness at 2.05.

When we drop countries that do not follow the conditional CAPM, we note that the portfolio's co-skewness rises to 2.11 with equal weights and 2.30 with GDP based weights. Larger countries including Brazil and India have weights above 15% of the total portfolio when weighting is done by GDP. Of the total skewness, 1.36 is contributed by local currency co-skewness under equal weights and 1.51 under GDP based weights.

This brief exercise highlights two things. Firstly, despite the fact that most emerging markets fail to outperform the Russell 2000 index in dollar terms, they remain an attractive investment through their contribution to a US based portfolio's co-skewness. Secondly, the overall portfolio's co-skewness is primarily driven by co-skewness contributed by local currency index returns as opposed to the returns on currency. Thus, we foresee emerging market indices, particularly those listed in the MSCI Emerging Market Index, to continue being attractive means of increasing portfolio skewness for US based investors, particularly those considering medium to small capitalization stocks.

6. Conclusion.

In this article we have considered the conditional CAPM as a means of better understanding emerging market equities. Our results indicate that the conditional CAPM is a worthy contender for emerging market equities as a majority of emerging market economies considered in our sample show support the model, particularly when considered from the perspective of a US mid-small cap investor.

We also note economic and statistical factors that contribute to the conditional CAPM model being the relevant choice for an emerging market. Consistent with previous approaches to emerging markets, we find evidence that, whilst emerging markets do not always outperform our chosen US index, they do contribute to a better profile (and, implicitly, higher expected utility) as far as higher moments are concerned. We provide further analysis which allows us to look into co-skewness from currency returns and from domestic equity returns. Whilst this approach does not lead to obvious global factors, it does give us insights into the economies and currency regimes of specific countries. This is consistent with the view that Emerging Market country return have country-specific risk rather than the usual common factors (the Russell 2000 in this instance).

Our article suggests branching avenues of research. While we have considered the market timing model, it may be worth considering other forms of analytical structures (implying different market structures) to evaluate the conditional CAPM for emerging markets; although some structures are easier to empirically estimate than others as indicated by Rabindranath et al (2018), it is nevertheless an interesting proposition. Secondly, profitability of investments in emerging market equities with the conditional CAPM may be worth considering. Finally, not only does our methodology allow us to analyse emerging markets from a portfolio optimisation perspective but it may also be employed to specific emerging markets as a case study. Deeper analysis on the breakdown between foreign exchange and currency returns may prove to be revealing for some emerging market equities. Thus, our research provides a practical means of modelling emerging market equities from the perspective of an international investor while opening up further avenues of research that could use our methodology.

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