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Pricing emerging market stock returns: An update

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ABSTRACT

This paper tests how effective global models are at pricing the cross section of emerging market (EM) stock returns over a recent post-liberalization period. We apply the tests of Kan et al. (2009). Our results show that conditional models and currency factors do perform better than unconditional models and single factor models and there are some differences in the models in the two subperiods of our data. The important implication of this paper for international investors is none of our results are significant when we allow for model misspecification and none of the alternative models specifically outperform the World CAPM.

1. Introduction

Emerging market (EM) stocks are characterised in early studies by large average returns but low correlation with developed markets (Harvey, 1995a), and are promoted on their ability to improve mean-variance efficiency for investors pursuing portfolio diversification (Erb et al., 1997). However, as investment uncertainty reduces, risk and returns fall in line with those offered in developed markets (Bekaert and Harvey, 2003).[1] This paper tests how effective global models are at pricing the cross section of EM stock returns over a recent post-liberalization period and in two successive subperiods in our data. Studies on developed markets present evidence in support of a global asset pricing model (Harvey, 1991), those on EM find much weaker support for global determinants of risk, (Harvey, 1995a,b; Bilson and Brailsford, 2002).

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[1] Increasing EM integration with the world economy has two important implications on international investment (Fernandez, 2003). Firstly, it is predicted that correlations between the returns in emerging and developed markets will increase (Erb et al., 1998). Secondly, with increasing integration, global risk factors will become increasingly applicable in the pricing of EM stocks, so global asset pricing models should increase in their ability to explain the cross section of EM returns (Bekaert and Harvey, 2003).

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Bekaert and Harvey (2002) find an increase in correlation between EM and developed capital markets in the post-liberalization period. They show that EM betas with the world portfolio increase on average two and a half times between the pre- and post-liberalization periods, indicating significant increased EM responsiveness to global market risk. Despite these ostensibly substantial increases, Bekaert and Harvey (2002) nevertheless conclude that EM correlations with the developed world are still low enough to provide the global investor with significant portfolio diversification. However, Fernandez (2003) suggests that EM stocks' exposure to the global market is no longer significantly different from that of developed market stocks. Several recent studies have shown a number of other important factors in EM stock market returns including time variation, local information variables and currency risk. Chaieb and Errunza (2007) and Carrieri et al. (2007) show that local information variables explain EM stock returns to a greater extent than developed market returns. Carrieri et al. (2007) examine the relevance of both time-varying global and local market risk on the expected returns and find evidence of significant time variation in the price of both local and global market risk. This suggests that specifying a global asset pricing model that holds period-by-period significantly improves the mean-variance efficiency of the world portfolio, and thus the model's ability to explain EM returns. Moreover, the results of Carrieri et al. (2007) imply that implementing unconditional models in EM will result in misspecification. In terms of currency risk Carrieri et al. (2006a) find that EM currency risk (measured in real terms) is priced separately from other EM risks and represents a significant proportion of equity returns in both developed and EM.

Taking into account the above sequence of prior findings, the expectation of this paper is that–with an even more up-to-date dataset and taking into account time variation, information variables and currency risk–asset pricing models with global determinants of risk will do an even better job at explaining the cross section of EM stock returns. We test how effective global models are at pricing the cross section of EM stock returns over the most recent post-liberalization period. We use two-stage cross-sectional regression approach of Fama and MacBeth (1973) to calculate the performance of the models. We apply the recent tests of Kan et al. (2009) which allows for possible model misspecification. We examine the performance of the models focusing monthly portfolio return data on twenty EM countries from 1995 to 2008 and examining two subperiods in our data (1995–2001 and 2002–2008) to consider if there have been changes over our sample period. Eight asset pricing models are tested in this paper. Four of them are unconditional models. These are (1) simple CAPM with developed world index, (2) simple CAPM with emerging world index, (3) currency model with developed world index and three currency factors (we use the excess $ returns on three currencies for the German DM, Japanese Yen, and U.K. £ sterling), (4) currency model with emerging world index and three currency factors. The remaining four are conditional models. We estimate the conditional models by adding a global information variable as a separate factor to each model. We considered the lagged dividend yield on the Datastream world equity index, the lagged return on the one-month U.S. Treasury Bill, and the lagged monthly growth of the OECD G7 industrial production index (excluding construction).

Our main results can be summarised as follows. There is a wide spread in the performance across the eight models in terms of the estimated R^2, but typically the conditional versions of the models do a better job than the unconditional versions of the models in terms of the cross-sectional R^2. The factor models including currency risk perform better than the single factor model. However, when we allow for model misspecification there are no significant differences in the cross-sectional R^2. Therefore there does not appear to be much difference between the global factor models and the corresponding EM factor models. We find the performance of the linear factor models does vary between the two subperiods, with better performance by the models perform in the first subperiod. The results suggests that for the overall sample period, both conditioning information and the use of the currency factors improve the models. For the overall period there are no significant factors in any of the unconditional models. For the conditional models, there is a significant impact for the lagged dividend yield. The currency factors play a greater role in the second subperiod. However, the statistical significance of these factors is not robust when we allow for potential model misspecification due to high sampling variation. The important result for international investors and asset pricing in EM is that over this recent post-liberalization period our results suggest that when we control for possible model misspecification as in Kan et al. (2009) none of the models outperform the world CAPM.

The rest of this paper is structured as follows. Section 2 outlines the models and the research method. Section 3 describes the dataset. Empirical results are presented in Section 4. Conclusions are provided at the end.

2. Models and research method

2.1. Two-stage cross-sectional regression approach

A linear beta model such as the CAPM predicts that there is an exact linear relation between expected returns of the N assets and the corresponding betas relative to the K factors. This relation is given by:

$$E(r_i) = \gamma_0 + \Sigma_{k=1}^{K} \beta_{ik}\gamma_k \quad \text{for} \quad i = 1, \ldots.., N \tag{1}$$

where $E(r_i)$ is the expected return on asset i, γ_0 is the zero-beta return, β_{ik} is the beta of asset i with respect to factor k ($k=1,\ldots.,K$), γ_k is the factor risk premium of factor k, and K is the number of factors in the model.

An alternative representation of Eq. (1) is to use a linear relation between the expected returns and the covariances between the asset returns and corresponding factors rather than the betas (Kan et al., 2009). This relation is given by:

$$E(r_i) = \lambda_0 + \Sigma_{k=1}^{K} cov_{ik}\lambda_k \quad \text{for} \, i = 1, \ldots.., N \tag{2}$$

where λ_0 is the zero-beta return, cov_{ik} is the covariance between the returns of asset i and factor k, and λ_k is the price of covariance risk with respect to factor k. The choice between Eqs. (1) and (2) can be important when $K>1$ since the betas on a factor can depend upon the other factors in the model. This situation can make the interpretation of the factor risk premiums complicated when the factors in the model are correlated with one another. Focusing on the factor risk premiums addresses the question as to whether or not the factor is priced but it does not necessarily tell us whether the factor is useful in explaining cross-sectional returns given the other factors in the model.[2] Focusing on the factor price of covariance risk addresses the question as to whether the factor helps improves the explanatory power of the model in cross-sectional returns given the other factors in the model.

In our study we will focus on Eq. (2) and use the two-pass cross-sectional regression approach pioneered by Fama and MacBeth (1973) to evaluate the performance of the linear factor models in EM. Our study draws heavily on the recent study by Kan et al. (2009) which derives the asymptotic distribution of the parameters in Eqs. (1) and (2) under the null that the factor model is possibly misspecified.[3] Define R_t as a $(N, 1)$ vector of the monthly returns of N risky assets at time t and f_t is a $(K, 1)$ vector of the monthly values of the K factors at time t. In the first stage, we estimate the sample covariances between the N assets and K factors using T time-series observations by Maximum Likelihood (ML). Define C as a $(N, K+1)$ matrix which equals $(1_N, V_{21})$ where 1_N is a $(N, 1)$ vector of ones and V_{21} is a (N, K) matrix of sample covariances with respect to the K factors.

In the second stage, we estimate λ_0 and λ_k to minimize the weighted sum of squared pricing errors given by:

$$(u_2 - C\lambda)' W (u_2 - C\lambda) \tag{3}$$

where u_2 is a $(N, 1)$ vector of average returns on the N assets, λ is a $(K+1, 1)$ vector of the estimated zero-beta return and K factor prices of covariance risk, and W is a (N, N) weighting matrix. The u_2–$C\lambda$ vectors are the N pricing errors of the assets. If the model is well specified, then the pricing errors are equal to zero. Different weighting matrixes can be used in Eq. (3) to estimate λ. Ordinary Least Squares (OLS) estimation uses $W=I_N$ where I_N is the (N, N) identity matrix. In our study we use Generalized Least Squares (GLS)

[2] See Jagannathan and Wang (1998), Cochrane (2005) and Kan and Robotti (2009) for more discussion on this issue. A solution to this problem is to estimate betas on each factor in separate single regressions.

[3] See the related studies by Kan and Robotti (2009) and Li et al. (forthcoming) using the Hansen and Jagannathan (1997) distance measure framework.

estimation which sets $W = V_{22}^{-1}$ where V_{22} is the (N, N) sample covariance matrix of the N asset returns (ML).[4] The λ vector is estimated by:

$$\lambda = (C'WC)^{-1}C'Wu_2 \tag{4}$$

A useful diagnostic test of the model is the cross-sectional R^2 (Kandel and Stambaugh, 1995; Lewellen et al., forthcoming; Kan et al., 2009). The R^2 is calculated as:

$$R^2 = 1-(Q/Q_0) \tag{5}$$

where $Q_0 = u_2'Wu_2 - u_2'W1_N(1_N'W1_N)^{-1}Wu_2$, $Q = e'We$, and e is a $(N, 1)$ vector of N pricing errors. The R^2 lies between 0 and 1 and if the model is well specified the $R^2 = 1$.Kan et al. (2009) derive the asymptotic distribution of λ under the null of a potentially misspecified model under general distributional assumptions. The asymptotic distribution of λ is given by:

$$N(0_{K+1}, V(\lambda)) \tag{6}$$

where $V(\lambda) = \Sigma_{j=-\infty}^{\infty}E(h_t h_{t+j}')$. The h_t series is calculated as:

$$h_t = (\lambda_t-\lambda) + AG_t\lambda_1 + Hz_t u_t-(\lambda_t-\lambda)u_t \tag{7}$$

where $H = (C'WC)^{-1}$, $A = HC'W$, $\lambda_t = AR_t$, λ_1 are the prices of covariance risk for the K factors, $u_t = e'W(R_t - u_2)$, $G_t = V_{21} - (R_t - u_2)(f_t - u_1)'$, and $z_t = [0, (f_t - u_1)']'$. When the model is correctly specified, they point out that the last two terms in Eq. (7) disappear. The first term is the standard Fama and MacBeth (1973) standard error. The second term corrects for the estimation error of the covariances from the first stage (Shanken, 1992; Jagannathan and Wang, 1998). The third term captures the impact of model misspecification. The final term corrects for the use of an estimated weighting matrix. The $V(\lambda)$ is calculated from the time-series of h_t. We can correct for the impact of heteroskedasticity and serial correlation on the $V(\lambda)$ using the method of Newey and West (1987) among others.

Kan et al. (2009) derive the asymptotic distribution of the R^2 in Proposition 4 of their paper. They consider three cases. First, the model is true and explains all of the cross-sectional variation in expected returns ($R^2 = 1$). They define this case as the model specification test. Second, the model is misspecified but has some explanatory power in cross-sectional expected returns ($0 < R^2 < 1$). Third, the model has no explanatory power in cross-sectional stock returns ($R^2 = 0$). They show that for the test of $R^2 = 1$, the test statistic $T\ (R^2 - 1)$ has an asymptotic weighted χ^2 distribution with N-K-1 degrees of freedom. The test statistic for $R^2 = 0$ is given by TR^2 and has an asymptotic weighted χ^2 distribution with K degrees of freedom. They also demonstrate that when $0 < R^2 < 1$, the R^2 has an asymptotic normal distribution.

We use the results in Kan et al. (2009) to evaluate the performance of the linear factor models by examining the statistical significance of the factor prices of covariance risk and the GLS R^2 allowing for potential model misspecification. We also examine whether the N pricing errors are jointly equal to zero using the Q_c statistic in their study. The Q_c statistic is a generalized version of the Shanken (1985) test and is calculated as $e'V(e)^+e$ where $V(e)^+$ is the covariance matrix of the N pricing errors and + is the pseudo-inverse. The test statistic TQ_c has an asymptotic χ^2 distribution with N-K-1 degrees of freedom.

We further evaluate the linear factor models using the model comparison tests in Kan et al. (2009). They derive tests of the null hypothesis that two models have an equal R^2. The test statistic is given by:

$$\mathrm{Diff} = R_1^2-R_2^2 \tag{8}$$

[4] Most studies use the inverse of the residual covariance matrix from the time-series regressions used to estimate betas as the GLS weighting matrix. Lewellen et al. (forthcoming) show that the factor risk premiums and weighted sum of squared pricing errors are the same whether using the inverse of the residual covariance matrix or V_{22}^{-1} as the weighting matrix. Kan et al. (2009) point out another reason for using V_{22}^{-1} as the weighting matrix is that it facilitates model comparison when it comes to comparing the R^2 across models.

where R_1^2 and R_2^2 are the GLS R^2 for models 1 and 2. Their model comparison tests build on the earlier work of Vuong (1989) among others.[5] The challenge of the model comparison tests is that the relevant test depends upon whether the models are nested to one another or not and whether the models are well specified or not.

In the nested models case, model 2 includes a subset of the factors in model 1. Kan et al. (2009) show that $T(R_1^2 - R_2^2)$ has a weighted χ^2 distribution under the null hypothesis that the two models have the same R^2. For the non-nested models case, we use the asymptotic normal test of Proposition 9 in their study. This test assumes that both models do not have equal normalized stochastic discount factor values and both models are misspecified. An alternative approach is to use the sequential approach of Kan et al based on Lemma 4, Proposition 7, and Proposition 9 of their paper.[6] All of the test statistics are corrected for the effects of heteroskasticity and serial correlation using the method of Newey and West (1994) which uses an automatic lag selection without prewhitening.[7]

2.2. Linear factor models

The eight models in this paper compete on risk locality and time variation.[8] A global currency factor model is included to test the extent to which EM returns are driven by exchange rate risk.[9] Composite developed and emerging world portfolios represent the risk factors in the global and emerging models, respectively.

Our first four models are unconditional models.

1. "World CAPM" (WCAPM) — in this single factor model, the cross section of expected returns is assumed to be driven by the covariance of stock *i* with the world market portfolio.
2. "EM CAPM" (ECAPM) — in this single factor model, expected returns are driven by the covariance of stock *i* with the global EM portfolio.
3. "Currency World CAPM" (WCurr) — in this model, exchange rate risk is included and the world market portfolio is augmented with three currency factors (German DM, Japanese Yen, and U.K. £ sterling) that are collectively used to represent a global currency premium, giving rise to a four-factor model.
4. "Currency EM CAPM" (ECurr) — this four-factor model takes a similar to 3, but the world market portfolio is replaced with one restricted to EM.

We estimate the conditional models by adding a global information variable as a separate factor to each model. This approach is similar to Zhang (2006). We follow this approach to avoid the overfitting problem where conditional models do better due to the large number of factors in the model (Hodrick and Zhang, 2001). We do not scale the factors due to our sample size.

3. Data

All of our data is collected from Thomson Financial Datastream unless otherwise specified. We use the monthly returns of twenty EM equity indexes between February 1995 and December 2008 as our test assets. The countries are Argentina, Brazil, Chile, China, Columbia, Czech Republic, Hungary, India, Mexico, Peru, Philippines, Poland, Russia, South Africa, Thailand, Turkey, Venezuela, South Korea, Taiwan, and Malaysia. We use the U.S. dollar ($) returns of the Datastream EM equity indexes.[10] We select a start date of February 1995 since it gives a larger number of markets to use and the Datastream global EM index begins

[5] See the related model comparison tests in Kan and Robotti (2009) and Li et al. (forthcoming) using the Hansen and Jagannathan (1997) distance measures.

[6] We also use the sequential approach but find similar results to just using the asymptotic normal test and so only report the normal test.

[7] We implement all of our tests using the Matlab programs provided on Raymond Kan's web site.

[8] The former is a test of integration and examines whether EM stock returns are a function of risk factors specific to either developed or EM in aggregate. The latter examines whether allowing for time variation in the respective risk exposures and risk premia improves models' ability to explain the cross-sectional variation in average EM returns.

[9] Carrieri et al. (2006b) establish the importance of local currency risk as a pricing factor, separately from the local market factor (for a sample of seven EM countries in their models).

[10] We exclude Indonesia due to problems in the return data of the Datastream Indonesia market index.

Table 1
Summary statistics of EM and factors.

Panel A

Emerging markets	Mean	Standard deviation	Minimum	Maximum
Argentina	0.53	9.19	−30.40	27.49
Brazil	1.37	11.14	−33.23	39.72
Chile	0.58	6.18	−24.12	17.74
China	1.56	11.29	−26.57	48.35
Columbia	0.80	8.98	−24.78	27.10
Czech Republic	1.58	7.78	−26.86	23.58
Hungary	1.51	9.63	−39.13	39.81
India	1.04	9.24	−30.90	24.08
Mexico	1.26	7.89	−32.62	21.51
Peru	0.98	6.69	−29.40	31.42
Philippines	0.07	8.98	−27.14	48.68
Poland	1.31	10.06	−33.38	37.52
Russia	2.52	14.02	−48.15	46.97
South Africa	1.03	8.25	−35.35	19.78
Thailand	0.25	11.71	−32.51	40.83
Turkey	2.14	16.50	−40.83	70.53
Venezuela	0.89	12.42	−48.97	41.05
South Korea	0.91	11.95	−37.72	51.20
Taiwan	0.32	8.68	−22.43	28.23
Malaysia	0.53	9.45	−30.07	46.14

Panel B

Factors	Mean	Standard deviation	Minimum	Maximum
World	0.33	4.66	−16.44	11.50
Emerging	0.46	6.95	−28.05	15.04
DM	0.06	2.88	−9.41	9.79
Yen	−0.17	3.41	−10.53	16.52
£	0.11	2.34	−8.95	5.37

The table reports summary statistics of the monthly ($) returns of twenty EM equity indexes (Panel A) and the monthly excess returns of the factors (Panel B) in the global and EM factor models between February 1995 and December 2008. The summary statistics include the mean, standard deviation, minimum, and maximum. World is the Datastream world equity index. Emerging is the Datastream world EM equity index. DM, Yen, and £ are the currency factors for the German Deutsche Mark (DM), Japanese Yen, and British pound (£). All numbers are in monthly %.

at that point in time. Panel A of Table 1 reports summary statistics of the twenty EM equity indexes. The summary statistics include the mean, standard deviation, minimum, and maximum of monthly returns (%).

Panel A of Table 1 shows that there is a wide spread in the cross-sectional average returns across the EM. The average returns range between 0.07% (Philippines) and 2.52% (Russia). There is also a wide spread in volatility across markets. The volatility ranges between 6.18% (Chile) and 16.50% (Turkey). The markets with the highest average returns such as Russia, China, Turkey, and Brazil often have the highest volatility. The high volatility in EM is similar to earlier studies, such as Harvey (1995a) among others.

We use two global factor models and two EM models in our empirical analysis. We use the excess $ returns on the Datastream world equity index as the world market portfolio in the global models. We use the excess $ returns on the Datastream global EM index as the market portfolio in the EM models. The excess returns of the two market indexes are calculated relative to the returns on the one-month U.S. Treasury Bills available on Ken French's web site.

We form the currency factors using a similar approach to Dumas and Solnik (1995). We use the excess $ returns on three currencies for the German DM,[11] Japanese Yen, and U.K. £ sterling. The currency factors are formed as the $ return on a three-month Eurocurrency interest rate for that currency minus the one-month U.S. Treasury Bill return. Panel B of Table 1 includes summary statistics of the five factors.

[11] The monthly returns on the DM Eurocurrency rate and the DM/$ exchange rates are corrected for the impact of the Euro by Datastream.

Table 2
Performance of global and EM factor models.

	R^2	$p(R^2=1)$	$SE(R^2)$	$p(R^2=0)$	Q_c
WCAPM	3.01	72.58	8.04	45.79	6.39 (90.77)
WCurr	28.18	85.65	25.89	43.46	4.28 (95.33)
ECAPM	7.80	76.83	14.47	26.84	6.23 (91.81)
ECurr	27.88	84.61	24.50	48.17	4.44 (94.51)
Cond WCAPM	36.01	96.54	30.91	17.05	4.81 (96.57)
Cond WCurr	55.43	96.20	28.03	15.85	4.39 (92.15)
Cond ECAPM	35.87	96.17	30.28	19.25	4.89 (96.28)
Cond ECurr	54.88	96.16	28.33	27.36	4.48 (91.47)

The table reports the tests of model performance of four unconditional factor models and four conditional (Cond) factor models between February 1995 and December 2008. The models include two global factor models and two EM factor models. The lagged dividend yield on the World equity index is used as the information variable in the conditional models. R^2 is the Generalized Least Squares (GLS) cross-sectional R^2. The $p(R^2=1)$ and $p(R^2=0)$ columns are the empirical p values of the null hypotheses that the $R^2=1$ and the $R^2=0$. The $SE(R^2)$ column is the standard error of the R^2 for the case where $0<R^2<1$. Q_c is the test statistic that the pricing errors across the EM are jointly equal to zero with the corresponding p value in parentheses. All numbers are multiplied by 100. The test statistics are corrected for the effects of heteroskedasticity and serial correlation using the automatic lag selection (without prewhitening) method of Newey and West (1994).

Panel B of Table 1 shows that there is a positive average excess return on both the world index and the global EM index. The average excess returns on the three currency factors are smaller than either market index. However, none of the factors have an excess return more than two standard errors of zero.

To implement the conditional factor models, we are required to specify the information set of investors. We restrict our attention to three global information variables. We use the lagged dividend yield (DY) on the Datastream world equity index, the lagged return on the one-month U.S. Treasury Bill, and the lagged monthly growth of the OECD G7 industrial production index (excluding construction). Similar instruments are used in Ferson and Harvey (1999) and Zhang (2006) among others.

To explore the predictability of the three information variables, in unreported tests we run predictive regressions of the excess returns of the world equity index and global EM index on a constant and the three information variables. For the world equity index, the lagged dividend yield has a significant positive relation with the future monthly excess returns of the world market at the 10% significance level. Neither of the other two information variables have any significant relation with the world market. The Wald test can reject the null hypothesis that the slope coefficients on the three information variables are jointly equal to zero. The R^2 is 2.61% which suggests that there is a small amount of predictability in the world excess returns. In contrast to the world index, there is no significant predictability in the global EM index. None of the three information variables have any significant relation with the global EM excess returns and the R^2 from the predictive regression is only 1.94%. Due to these results, in our tests we use the lag DY as the information variable in our conditional factor models.

4. Empirical results

We begin our empirical analysis by estimating each of the eight linear factor models using GLS. Table 2 reports the model performance of the eight models for the whole sample period. The table includes the GLS R^2 (%), the p values (100) of the null hypotheses that the $R^2=1$ $(p(R^2=1))$ and $R^2=0$ $(p(R^2=0))$,[12] and the standard error (100) of the R^2 assuming that $0<R^2<1$. The final column includes Q_c (100) from Kan et al. (2009) which

[12] The p value of the test of $R^2=0$ is calculated by imposing the null hypothesis that the estimated factor risk premiums are equal to zero when estimating the covariance matrix of the factor risk premiums.

tests if the pricing errors of the N assets are jointly equal to zero and the corresponding p value (100) in parentheses.

Table 2 shows that there is a wide spread in the R^2 across the eight models. The R^2 ranges between 3.01% (WCAPM) and 55.43% (Cond WCurr). The conditional versions of the models do a better job than the unconditional versions of the models in terms of a higher R^2. The poorest performing models are the WCAPM and ECAPM models. There does not appear to be much difference between the global factor models and the corresponding EM factor models in terms of the R^2.

The standard errors of the R^2 in Table 2 are big highlighting the large sampling variation in the GLS R^2. The standard errors are larger for the conditional models. The large sampling variation in the GLS R^2 means that we cannot reject the null hypothesis that the $R^2=1$ or the $R^2=0$ for any model. These two extremes imply that for any model we cannot reject the null that the model is true or the model cannot explain any of

Table 3
Performance of global and EM factor models: subperiod results.

Panel A					
Subperiod 1	R^2	$p(R^2=1)$	$SE(R^2)$	$p(R^2=0)$	Q_c
WCAPM	24.05	87.53	22.67	4.08	11.60 (94.34)
WCurr	31.55	82.65	28.21	0	8.40 (95.84)
ECAPM	22.47	88.24	23.95	7.15	11.29 (95.06)
ECurr	26.98	77.61	27.11	52.03	9.78 (91.91)
Cond WCAPM	29.85	85.96	24.32	16.51	8.84 (97.88)
Cond WCurr	36.01	80.83	29.20	47.81	6.86 (97.37)
Cond ECAPM	30.54	89.41	25.42	16.27	9.22 (97.34)
Cond ECurr	33.50	80.28	23.48	58.15	8.06 (94.60)
Panel B					
Subperiod 2	R^2	$p(R^2=1)$	$SE(R^2)$	$p(R^2=0)$	Q_c
WCAPM	0.22	2.62	1.58	78.70	23.36 (35.43)
WCurr	25.08	25.52	28.98	32.36	4.41 (99.86)
ECAPM	1.03	2.78	3.47	59.68	23.70 (33.82)
ECurr	23.31	25.61	28.76	36.49	3.40 (99.97)
Cond WCAPM	0.74	1.52	4.49	92.91	23.43 (29.08)
Cond WCurr	25.24	37.63	29.11	49.28	16.66 (45.03)
Cond ECAPM	1.31	2.31	5.61	88.35	27.82 (13.77)
Cond ECurr	23.61	26.72	29.18	49.71	10.61 (83.67)

The table reports the tests of model performance of four unconditional factor models and four conditional (Cond) factor models for subperiods between February 1995 and December 2001 (Panel A) and January 2002 and December 2008 (Panel B). The models include two global factor models and two EM factor models. The lagged dividend yield on the World equity index is used as the information variable in the conditional models. R^2 is the Generalized Least Squares (GLS) cross-sectional R^2. The $p(R^2=1)$ and $p(R^2=0)$ columns are the empirical p values of the null hypotheses that the $R^2=1$ and the $R^2=0$. The $SE(R^2)$ column is the standard error of the R^2 for the case where $0<R^2<1$. Q_c is the test statistic that the pricing errors across the EM are jointly equal to zero with the corresponding p value in parentheses. All numbers are multiplied by 100. The test statistics are corrected for the effects of heteroskedasticity and serial correlation using the automatic lag selection (without prewhitening) method of Newey and West (1994).

the variation in cross-sectional stock returns. Likewise the Q_c statistic cannot reject the null hypothesis that the pricing errors across the twenty EM are jointly equal to zero for any model. The large sampling variation in the GLS R^2 is similar to Kan et al. (2009) for U.S. stock returns.

We next examine the performance of the eight models during the two subperiods. Table 3 reports the performance of the eight models between the February 1995 and December 2001 (Panel A) and January 2002 and December 2008 (Panel B) subperiods. The table contains the same information as Table 2.

Table 3 suggests that the performance of the linear factor models varies between the two subperiods. The models perform better in the first subperiod in terms of higher R^2. In the first superiod, the R^2 ranges between 24.05% (WCAPM) and 36.01% (Cond WCurr). As with the overall sample, the conditional factor models have a higher R^2 than the corresponding unconditional factor models. There is a marginal increase

Table 4
Prices of covariance risk for unconditional factor models: subperiod results.

Panel A				
Subperiod 1	WCAPM	WCurr	ECAPM	ECurr
λ_o	−0.91	−0.77	−1.12	−0.92
t_{cs}	(−1.73)*	(−1.34)	(−2.44)**	(−1.44)
t_{pm}	(−1.29)	(−0.98)	(−1.80)*	(−0.97)
λ_{mkt}	5.71	5.06	3.51	2.52
t_{cs}	(2.01)**	(1.34)	(1.86)*	(1.05)
t_{pm}	(1.98)**	(1.21)	(1.89)*	(1.02)
λ_{DM}		−6.94		−6.12
t_{cs}		(−0.57)		(−0.48)
t_{pm}		(−0.47)		(−0.38)
λ_{Yen}		−2.05		−0.19
t_{cs}		(−0.34)		(−0.03)
t_{pm}		(−0.29)		(−0.03)
λ_{Pound}		1.13		−2.20
t_{cs}		(0.06)		(−0.12)
t_{pm}		(0.05)		(−0.08)
Panel B				
Subperiod 2	WCAPM	WCurr	ECAPM	ECurr
λ_o	1.05	0.67	0.97	0.61
t_{cs}	(1.90)*	(1.02)	(1.87)*	(0.94)
t_{pm}	(1.49)	(0.92)	(1.57)	(0.90)
λ_{mkt}	0.82	−5.03	1.21	−2.78
t_{cs}	(0.27)	(−0.96)	(0.50)	(−0.75)
t_{pm}	(0.26)	(−1.00)	(0.54)	(−0.79)
λ_{DM}		32.03		30.01
t_{cs}		(1.91)*		(1.72)*
t_{pm}		(1.25)		(1.13)
λ_{Yen}		−31.37		−30.20
t_{cs}		(−2.09)**		(−1.76)*
t_{pm}		(−1.32)		(−1.49)
λ_{Pound}		−25.33		−21.02
t_{cs}		(−1.79)*		(−1.40)
t_{pm}		(−1.02)		(−0.95)

*Significant at 10%.
**Significant at 5%.
The table reports the GLS estimates of the zero-beta rate (λ_0) and the prices of covariance risk in four unconditional linear factor models for subperiods between February 1995 and December 2001 (Panel A) and January 2002 and December 2008 (Panel B). The models include two global factor models and two EM factor models. The λ_{mkt} term refers to the world market index for the WCAPM and WCurr models and the world EM index for the ECAPM and ECurr models. The remaining λ terms refer to the currency risk factors for the German Deutsche Mark (DM), Japanese Yen, and British pound (£). The t_{cs} statistic is the value of the t-statistic under the null of a correctly specified model. The t_{pm}-statistic is the value of the t-statistic under the null of a possibly misspecified model. The test statistics are corrected for the effects of heteroskedasticity and serial correlation using the automatic lag selection (without prewhitening) method of Newey and West (1994).

in the R^2 between the global models and the local models for three of the four cases. There is much narrower range in R^2 across the factor models in the first subperiod.

The R^2s in Panel A of Table 3 have large sampling variation as reflected in the large standard errors. The specification test of $R^2=1$ cannot be rejected for any model. However we can reject the null hypothesis of $R^2=0$ at the 10% significance level for the WCAPM, WCurr, and ECAPM models which suggests that these

Table 5
Prices of covariance risk for conditional factor models: subperiod results.

Panel A				
Subperiod 1	WCAPM	WCurr	ECAPM	ECurr
λ_o	−0.95	−0.81	−1.15	−0.97
t_{cs}	(−1.56)	(−1.30)	(−1.80)*	(−1.39)
t_{pm}	(−1.27)	(−1.10)	(−1.47)	(−1.08)
λ_{DY}	91.99	81.97	105.10	96.99
t_{cs}	(0.88)	(0.81)	(1.02)	(0.98)
t_{pm}	(0.73)	(0.61)	(0.89)	(0.77)
λ_{mkt}	4.63	4.32	2.92	2.22
t_{cs}	(1.45)	(1.02)	(1.34)	(0.86)
t_{pm}	(1.24)	(1.04)	(1.26)	(0.76)
λ_{DM}		−6.69		−5.69
t_{cs}		(−0.55)		(−0.45)
t_{pm}		(−0.49)		(−0.37)
λ_{Yen}		−1.93		−0.42
t_{cs}		(−0.32)		(−0.07)
t_{pm}		(−0.31)		(−0.07)
λ_{Pound}		2.78		0.41
t_{cs}		(0.15)		(0.02)
t_{pm}		(0.12)		(0.02)
Panel B				
Subperiod 2	WCAPM	WCurr	ECAPM	ECurr
λ_o	1.01	0.68	0.95	0.62
t_{cs}	(1.87)*	(0.92)	(2.34)**	(0.87)
t_{pm}	(1.51)	(0.80)	(1.42)	(0.77)
λ_{DY}	−21.07	−13.76	−15.89	−19.43
t_{cs}	(−0.25)	(−0.15)	(−0.20)	(−0.22)
t_{pm}	(−0.22)	(−0.14)	(−0.17)	(−0.19)
λ_{mkt}	0.76	−5.11	1.06	−2.92
t_{cs}	(0.26)	(−1.10)	(0.62)	(−0.91)
t_{pm}	(0.25)	(−1.10)	(0.46)	(−0.88)
λ_{DM}		32.63		31.02
t_{cs}		(1.75)*		(1.67)*
t_{pm}		(1.28)		(1.25)
λ_{Yen}		−30.91		−29.76
t_{cs}		(−1.78)*		(−1.72)*
t_{pm}		(−1.32)		(−1.24)
λ_{Pound}		−26.78		−23.13
t_{cs}		(−1.49)		(−1.37)
t_{pm}		(−1.02)		(−0.99)

*Significant at 10%.
The table reports the GLS estimates of the zero-beta rate (λ_0) and the prices of covariance risk in four conditional linear factor models for subperiods between February 1995 and December 2001 (Panel A) and January 2002 and December 2008 (Panel B). The models include two global factor models and two EM factor models. The lagged dividend yield (DY) on the World equity index is used as the information variable in the conditional models. The λ_{DY} term refers to the information variable in the conditional models. The λ_{mkt} term refers to the world market index for the WCAPM and WCurr models and the world EM index for the ECAPM and ECurr models. The remaining λ terms refer to the currency risk factors for the German Deutsche Mark (DM), Japanese Yen, and British pound (£). The t_{cs} statistic is the value of the t-statistic under the null of a correctly specified model. The t_{pm}-statistic is the value of the t-statistic under the null of a possibly misspecified model. The test statistics are corrected for the effects of heteroskedasticity and serial correlation using the automatic lag selection (without prewhitening) method of Newey and West (1994).

models have some explanatory power in the cross-sectional EM returns. The Q_c statistic is unable to reject the null hypothesis of zero pricing errors for any model in the first subperiod.

In Panel B of Table 3, many of the models have poorer performance in the second subperiod as reflected in the lower R^2. The real contrast in performance in the second subperiod is between the models with currency factors in them and those without. There is very little difference in R^2 between the conditional and unconditional models or between the global and local models. The R^2 ranges between 0.22% (WCAPM) and 25.24% (Cond WCurr). We are unable to reject the null hypothesis of the $R^2=0$ for any factor model. However, the model specification test does reject the null hypothesis of the $R^2=1$ for the WCAPM, ECAPM, Cond WCAPM, and Cond ECAPM models. The Q_c statistic is unable to reject the null hypothesis of zero pricing errors for any model in the second subperiod.

The results in Tables 2 and 3 highlight the difficulty of detecting any significant results due to the large sampling variation in the test statistics. The results suggests that for the overall sample period, both conditioning information and the use of the currency factors improve the R^2 of the models. This result is similar to Zhang (2006) among others. The role of conditioning information is more marginal in the two subperiods. However, the currency factors do play a more important role in the second subperiod as the specification test can reject the unconditional and conditional versions of the CAPM.

We next examine the parameter estimates and statistical significance of the zero-beta rate and the price of the covariance risk of each factor in the overall period and the two subperiods. For the overall period there are no significant factors in any of the unconditional models. For the conditional models, there is a significant negative λ on the lagged dividend yield using the Fama and MacBeth (1973) *t*-statistics in all models. However, the statistical significance disappears if we either correct only for estimation error in the covariances between the asset returns and factors or if we correct for both estimation error and allow for potential model misspecification. Tables 4 and 5 reports the λ coefficients and the corresponding *t*-statistics in parentheses for the zero-beta rate and the factors for the two subperiods (Panel A is the first subperiod and Panel B is the second subperiod). The *t*-statistics are estimated under the null of a correctly specified model (t_{cs}) and under the null that the model is possibly misspecified (t_{pm}). Table 4 refers to the unconditional models and Table 5 refers to the conditional models.

Panel A of Tables 4 and 5 shows that there is a negative zero-beta rate for all the factor models. There is significant negative zero-beta rate in the ECAPM and Cond ECAPM models using the t_{cs} statistic but the statistical significance disappears when we allow for potential model misspecification. The negative zero-beta rates suggest evidence of model misspecification. For the WCAPM and ECAPM models, there is a significant price of covariance risk using the world market and global EM indexes. The significant λ on these factors suggest they play an important role in explaining EM returns in the first subperiod and explains the higher R^2 for the WCAPM and ECAPM models in the first subperiod relative to the second subperiod. The statistical significance of the price of covariance risk of the market disappears in the conditional models and the currency models. None of the factors are significant in these models.

In Panel B of Tables 4 and 5 there is a large positive zero-beta rate in all of the factor models. There is a significant positive zero-beta rate in the WCAPM, ECAPM, Cond WCAPM, and Cond ECAPM models using the t_{cs} statistic. However, the statistical significance disappears when we correct for potential model misspecification. The currency factors play a greater role in the second subperiod. There is a significant price of covariance risk relative to the three currency factors in the WCurr model at the 10% significance level using the t_{cs} statistic. There is a significant positive λ on the German DM and a significant negative λ on the Yen and £ currency factors in the WCurr model. The German DM and Yen remain significant in the ECurr, Cond WCurr, and Cond ECurr models. This result suggests that these factors play a useful role in explaining EM returns and explains the higher R^2 for these models. However, the statistical significance of the currency factors is not robust when we allow for potential model misspecification. The sign of the price of covariance risk on the market is negative in the Currency models which highlights problems with these models.

Our final test is to examine model comparison tests that consider whether the R^2 of two models are jointly equal to each other for every pair of models. Table 6 presents the difference in R^2 (100) between models 1 and 2 where model 1 refers to the columns of the table and model 2 refers to the rows of the table. The corresponding *p* values (100) of the test of equal R^2s between the two models is in parentheses below. The results are reported for the overall period. If the difference in R^2 is positive, then the model on the column has a higher R^2 than the model in the row.

Table 6
Tests of Equal GLS R^2s.

	WCurr	ECAPM	ECurr	Cond WCAPM	Cond WCurr	Cond ECAPM	Cond ECurr
WCAPM	25.16	4.79	24.87	33.00	52.42	32.86	51.87
	(46.97)	(56.21)	(35.52)	(18.07)	(41.30)	(43.67)	(26.76)
WCurr		−20.37	−0.29	7.84	27.26	7.69	26.70
		(43.61)	(96.79)	(86.29)	(28.60)	(87.07)	(53.14)
ECAPM			20.08	28.21	47.63	28.07	47.08
			(56.99)	(51.19)	(25.08)	(20.93)	(43.06)
ECurr				8.13	27.55	7.98	26.99
				(86.33)	(50.00)	(86.51)	(26.07)
Cond WCAPM					19.42	−0.14	18.87
					(60.26)	(96.18)	(47.61)
Cond WCurr						−19.56	−0.55
						(46.56)	(83.58)
Cond ECAPM							19.01
							(60.27)

The table reports the tests of the differences in the GLS R^2 for two models for every pair of model of four unconditional factor models and four conditional (Cond) factor models between February 1995 and December 2008. The models include two global factor models and two EM factor models. The lagged dividend yield on the World equity index is used as the information variable in the conditional models. The table includes the differences in R^2 (100) and the p value of the null hypothesis that the difference in R^2 between the two models are equal to one another. The test statistics allow for possible model misspecification and are corrected for the effects of heteroskedasticity and serial correlation using the automatic lag selection (without prewhitening) method of Newey and West (1994).

Table 6 shows that there are no significant differences in R^2 between any pair of models for the whole sample period. This result holds even where there are large differences in R^2 between certain models. An example of this large difference is between the WCAPM and Cond WCurr models or the WCAPM and Cond ECurr models in the overall sample period where the difference in R^2 exceeds 51%. However even here the difference is not statistically significant. The lack of statistical significance stems from the high sampling variation (Kan et al., 2009; Lewellen et al., forthcoming). These results suggest that there were no significant differences between the performance of the models when we allow for possible model misspecification. None of the models significantly outperform the WCAPM. Finally, similar results hold in both our subperiods.

5. Conclusion

This paper examines how effective global models are at pricing the cross section of EM stock returns over the most recent post-liberalization period. We consider eight linear asset pricing models on emerging capital markets on post-1995 data in two subperiods (1995–2001 and 2002–2008). We include a global currency premium and allow for time variation in the risk exposures and premium. We use two-stage cross-sectional regression approach of Fama and MacBeth (1973) to calculate the performance of the models. We apply the tests of Kan et al. (2009) which allows for possible model misspecification. We find that numerically, conditional models and currency factors do perform better than unconditional models and single factor models. There are wide differences in the estimated R^2 across our eight models. We find some differences in our two subperiods with better performance of the models in the first period and currency factors playing a more important role in the second period. However, none of our results are significant when we allow for model misspecification and none specifically outperform the World CAPM. The lack of statistical significance stems from the high sampling variation and highlights the difficulty of detecting any significant results due to the large sampling variation in the test statistics. The important implication of this paper for international investors in EM and for international asset pricing (for example in global asset allocation and hedging of portfolio risks) is that when we control for possible model misspecification as in Kan et al. (2009) none of the models outperform the world CAPM.

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