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Asset pricing models in emerging markets: Factorial approaches vs. information stochastic discount factor[☆]

Mariano González-Sánchez [*,1]

Business and Accounting Department, Faculty of Economic and Business, Paseo Senda del Rey, 11. 28040 Madrid, Spain
Universidad Nacional de Educación a Distancia (UNED), Spain

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ABSTRACT

The factorial asset pricing models generally performs poorly in emerging markets. This prediction bias implies anomalies. This study analyzes whether it is consequence of ignoring other source of risk. We apply a non-parametric approach (stochastic discount factor) to improve the forecasts of the usual factorial models. For a sample of 26 emerging equity markets, we find that the information portfolio built from the stochastic discount factor shows better goodness of fit of emerging market and, only the factor that accounts value stocks versus growth stocks is relevant to emerging equity markets, specifically, it is a sensitivity measure at risk.

1. Introduction and background

The seminal works about emerging stock markets, Harvey (1995) and Bekaert and Harvey (1997), showed that there is a value premium in emerging market equity returns. As consequence, some empirical works on this matter arise.

Most of the empirical studies on asset valuation in emerging markets focus on testing the validity of factor models, specifically using the 5-factor model (see Fama and French (2015)) and also including the momentum factor (Fama and French, 2018). Thus, the factors usually tested are: excess returns on markets ($Mkt - Rf$) over risk-free rate (Rf), size (SMB or small minus high market cap), value portfolios (HML or high minus low book-to-market ratio), profitability (RMW or robust minus weak), investment factor (CMA or conservative minus aggressive) and momentum factor (WML or returns for winner portfolios for emerging markets minus returns for loser portfolios).

In this context of factor models, Cakici et al. (2013) find strong evidence for the value effect in all emerging markets and also. the momentum effect for all but Eastern Europe. Lin (2017) is an empirical evaluation of the five-factor model from Chinese stock market, and similar, Nartea et al. (2017) analyzes Chinese stock markets using firm-level Fama–MacBeth cross-sectional regressions and, find evidence that stocks with high maximum daily returns in the previous month, perform poorly in the current month, but this effect does not present a reversal to idiosyncratic volatility effect, unlike developed markets. Leite et al. (2018) find that the four- and five-factor models perform better than the three-factor model. Foye (2018) shows that there is a pronounced value premium for all three regions (Asian, Eastern Europe and Latin America) and HML is the only one of the five factors that is not redundant

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* Correspondence to: Universidad Nacional de Educación a Distancia (UNED), Spain.
E-mail address: mariano.gonzalez@cee.uned.es.
1 Assistant Professor of Financial Economic and Accounting.

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in any of the regions and, RMW factor only influences in Eastern Europe and Latin America. Hanauer and Lauterbach (2019), on a sample of 28 emerging stock markets, do not find a positive cross-sectional relationship between risk and return. Lin et al. (2020) use six-factor model from the Chinese stock market and, find that the characteristics of companies possess useful information to effectively predict future stock return. Butt et al. (2021) study, in 19 emerging market countries, the lower momentum returns in emerging markets and find that momentum returns are lower in more risk averse emerging market countries. However, for the Russian stock market, when Teplova and Tomtosov (2021) combined momentum factor and high volume into a composite factor, the results of momentum improving. Safiullah and Shamsuddin (2021) find that the Fama–French five-factor model is not adequate for pricing Islamic equities. Mosoeu and Kodongo (2021), using the Fama–French five-factor asset-pricing model on average stock returns for selected emerging and developed equity markets, find that the profitability factor is the most useful for explaining the cross-section of emerging markets equity returns. For Indian stock market, Dharania et al. (2021) found that search attention index explains the variation in the excess return of stocks as well as the market, size, value, and momentum factors.

As a consequence of the questionable results of the usual asset pricing models in emerging markets, Stocker (2016) analyzes a possible relationship between economic freedom of countries and level equity return factors and using Fama and MacBeth (1973) regressions, found a relationship between the economic freedom factor and the excess return. Also, Stereńczak et al. (2020) find that Illiquidity is less important in asset pricing from emerging markets. Finally, González-Sánchez (2021) used wavelet decomposition of the observed return to calculate sensitivity to risk five factors and obtain a term structure for risk factor premiums and finds that only the market risk factor show a term structure for risk premiums, while the other four factors present risk premiums independent of the term. In short, from the empirical evidences, there is no consensus on what factors influence emerging stock markets and, in general these studies find anomalies (see Foye (2018)) that supposes linear asset pricing models with statistically significant intercepts, or lack of correlation between return and risk, or negative market risk premiums. Therefore, emerging equity markets show unique characteristics that are not adequately captured by standard risk factors or/and linear factor models. As a consequence of the above, the question arises as to whether a nonparametric model would improve the results of factor models for emerging markets.

Usually, the non-parametric pricing method supposes the estimate of the pricing kernel, for example a model-free estimation of stochastic discount factor (SDF). Iqbal et al. (2010) estimate SDF from Pakistan stock market using sequential generalize method of the moments but assuming the five factor model. Conversely, we use Gosh et al. (2017) approach, without assuming underlying factor model, to estimate information SDF and then, we recovery the expected return of information portfolio and weights of each emerging market, since Gosh et al. (2017) shows better results than factorial models for developed markets.

The contributions of our study is twofold: first, from our best knowledge, this empirical studies is the first analysis of non-parametric information SDF on emerging equity markets, and second, we compare risk premiums from a non-parametric models with factorial models.

The remainder of the paper is organized as follows: Section 2 reviews the usual factorial models and describes the proposal methodology. Section 3 discusses the data, 26 stock market indexes from Asia, Eastern Europe and Latin America for the period 2004–2019. Section 4 analyzes the empirical results. Section 5 presents our concluding remarks.

2. Methodology

Usually, empirical research about emerging equity market estimate a linear models as follows:

$$R^e_{t,i} = \alpha_{0,i} + \sum_{j=1}^{J} \beta_{j,i} \cdot F_{j,t} + u_{t,i} \tag{1}$$

Where $R^e_{i,t}$ is excess return of asset i for period t over risk-free rate (Rf), F_j is each risk factors and $\beta_{j,i}$ is the sensitivity of asset i to factor j. So, the empirical studies estimate expression-(1) by ordinary least squares (with standard deviation of parameters adjust to autocorrelation and heteroscedasticity) and, the results show anomalies ($\alpha_{0,i} \neq 0$) and low goodness of fit of the model (R^2). After, as Fama and MacBeth (1973), the premium of risk factors (λ) are estimated from the following cross-section regression:

$$\mu^e_i = \lambda_0 + \sum_{j=1}^{J} \lambda_j \cdot \hat{\beta}_{j,i} + e_{t,i} \tag{2}$$

Where μ^e_i is the average of excess return as proxy of expected return, and $\hat{\beta}_{j,i}$ is parameter estimated from expression-(1). In this case, another usual anomaly appears, the λ-risk portfolio market is negative.

Thereby, as Fama–French and momentum factors, revealing an information anomaly or significant $alphas$, we express non-parametric model by SDF and under a necessary and sufficient condition for no arbitrage, that is, the existence of a positive SDF that prices all payoffs such that:

$$1 = E_t\left[m_{t+1} \cdot R_{i,t+1}\right] \tag{3}$$

Where $E_t[\cdot]$ is operator of expected value with available information for time t and, m_{t+1} is SDF.

Gosh et al. (2017) use a model-free relative entropy minimization approach to estimate a SDF that prices the given cross-section. This approach allows us to use all the relevant information from priced risk factors in the form of a single time series for the SDF.

Table 1
Statistics resume of risk factors and excess return of emerging equity market indexes.

Panel A. Statistics of Risk Factors								
Factor	Observations	Mean	Median	Std. Dev.	Max	Min	Skewness	Kurtosis
Rf	192	0.11%	0.03%	0.13%	0.44%	0.00%	1.1949	0.2472
Mkt-Rf	192	0.90%	0.82%	5.87%	17.98%	−27.29%	−0.6366	2.8044
SMB	192	0.29%	0.52%	1.62%	4.21%	−6.94%	−0.839	2.1882
HML	192	0.64%	0.53%	1.56%	5.49%	−3.06%	0.0296	0.2708
RMW	192	0.44%	0.54%	1.13%	3.07%	−3.91%	−0.9527	1.73
CMA	192	0.46%	0.53%	1.33%	6.43%	−5.86%	−0.0672	4.8749
WML	192	0.82%	1.05%	2.58%	5.43%	−14.92%	−2.6928	12.847
Panel B. Emerging Equity Market Indexes								
Index	Country	Mean	Median	Std. Dev.	Max	Min	Skewness	Kurtosis
MERVAL	Argentina	2.35%	1.41%	10.19%	27.83%	−41.65%	−0.3725	1.8417
BOVESPA	Brazil	0.95%	0.67%	6.22%	16.95%	−24.88%	−0.2018	0.8947
IPSA	Chile	0.59%	0.34%	4.34%	16.09%	−10.54%	0.249	0.3227
Shanghai SE	China	0.58%	0.65%	7.88%	27.05%	−24.71%	−0.1794	1.4717
IGBC	Colombia	1.10%	0.96%	6.15%	19.22%	−19.13%	0.1051	1.6284
IPX	Czech Republic	0.33%	0.55%	5.62%	18.65%	−27.21%	−0.7728	4.4219
EGX30	Egypt	1.64%	1.75%	9.49%	36.56%	−33.27%	0.3068	2.0315
ASE	Greece	2.58%	0.48%	48.69%	67.48%	−82.02%	12.7307	27.0468
BUX	Hungary	0.92%	1.18%	6.20%	18.04%	−28.50%	−0.466	2.5184
SENSEX	India	1.11%	0.97%	6.17%	28.26%	−23.97%	−0.1799	3.0314
JCI	Indonesia	1.21%	1.52%	5.53%	20.12%	−31.50%	−1.0049	6.3919
KLCI	Malaysia	0.31%	0.60%	3.36%	13.54%	−15.30%	−0.3048	3.3236
IPC	Mexico	0.84%	0.78%	4.60%	12.89%	−17.93%	−0.419	1.1988
KSE100	Pakistan	1.29%	1.74%	6.68%	22.26%	−36.16%	−0.9746	5.1119
SP-BVL	Peru	1.35%	0.78%	8.23%	38.44%	−37.36%	0.3594	4.8015
PSEI	Philippines	0.91%	1.15%	5.00%	14.96%	−24.15%	−0.5625	2.9359
WSE	Poland	0.22%	0.39%	5.72%	18.95%	−23.50%	−0.2586	1.3356
QSE	Qatar	0.70%	0.45%	7.74%	29.48%	−25.70%	0.089	2.1032
MOEX	Russia	1.08%	1.45%	7.02%	22.06%	−28.85%	−0.5655	2.3879
TASI	Saudi Arabia	0.50%	0.99%	7.33%	19.59%	−25.83%	−0.4653	1.2281
JSE	South Africa	0.87%	1.02%	4.18%	12.16%	−14.11%	−0.1393	0.7386
KOSPI	South Korea	0.55%	0.72%	5.05%	13.51%	−23.21%	−0.5269	2.5666
TWSE	Taiwan	0.39%	0.86%	5.01%	14.99%	−18.98%	−0.3743	1.7724
SET	Thailand	0.42%	0.96%	5.30%	13.98%	−30.26%	−1.1317	5.2982
XU	Turkey	1.13%	1.59%	7.49%	22.84%	−23.33%	−0.1676	0.3229
ADX	United Arab Emirates	0.66%	0.10%	6.71%	42.99%	−17.63%	1.2601	8.5757

Therefore, a non-parametric approach to the recovery of the pricing kernel is an alternative to the ad-hoc construction of risk factors, and provides a model-free test of the efficient market hypothesis. The function to be optimized is defined as:

$$\arg\min_{\theta} \frac{1}{T} \sum_{t=1}^{T} \exp(\theta' \cdot \mathbf{R_t^e}) \tag{4}$$

Where $\mathbf{R_t^e}$ is a vector of excess market returns over risk-free rate (Rf_t) for N market assets and each time ($t = 1, \dots, T$), θ is the vector of Lagrange multipliers that solve the unconstrained convex problem and, SDF is estimated as follows:

$$E_t\left[m_{t+1}\right] = \frac{exp(\theta' \cdot \mathbf{R_t^e})}{\sum_{t=1}^{T} exp(\theta' \cdot \mathbf{R_t^e})} \tag{5}$$

We use Eq.-(5) to recover the time series of the SDF. So, for a given cross section of asset returns, we divide the time series of returns into rolling subsamples of length T and, in each subsample, estimate the vector of Lagrange multipliers by solving the minimization. From these estimated parameters, we obtain the out-of-sample information SDF for the subsequent each period, using equation $E_t(m_{t+1})$ and $R_{m,t} = \ln(1 + m_t)$, where the expected return of information-SDF portfolio identifies a novel source of risk, potentially, not captured by factor models.

To build this portfolio, we run this regression of estimate SDF on excess return of assets:

$$m_t = a_0 + \sum_{i=1}^{N} b_i \cdot R_{t,i}^e + v_{t,i} \tag{6}$$

And then, the weight of each k-asset is estimated as: $w_k = \frac{b_k}{\sum_{i=1}^{N} b_i}$.

Finally, we also regress estimate SDF return on usual risk factors ($j = 1, \dots, J$) to verify whether some of them is an explanatory factor of the information-SDF portfolio:

$$R_{m,t} = c_0 + c_j \cdot F_{j,t} + \epsilon_{m,t} \tag{7}$$

Table 2
Factorial models with higher and lower goodness of fit.

Country	Index	R^2	Value R^2	Date	$Mkt - Rf$	SMB	HML	RMW	CMA	WML
Argentina	MERVAL	min.	16.97%	Oct-17	0.5326	1.4859	0.0876	0.1922	−1.1635	−1.2965
Argentina	MERVAL	max.	86.31%	Aug-10	0.7296(**)	0.0024	1.1996(**)	−1.204(*)	−0.194	−0.1174
Brazil	BOVESPA	min.	70.68%	Oct-19	0.7891(**)	0.2144	0.5964	−1.8188(**)	0.5824	−0.4747
Brazil	BOVESPA	max.	87.27%	Nov-08	0.8135(**)	−0.5796(**)	1.2457(**)	0.0346	−0.1213	−0.0946
Chile	IPSA	min.	27.32%	Jan-08	0.4127(**)	0.2486	0.0429	0.1682	−0.23	0.2218
Chile	IPSA	max.	60.21%	Sep-14	0.7878(**)	0.1597	−1.0742(**)	0.5342	0.2719	−0.155
China	Shanghai SE	min.	16.52%	Mar-15	0.0822	0.184	1.2748	0.0924	−0.4513	−0.3466
China	Shanghai SE	max.	55.88%	Jan-19	1.0974(**)	0.9271	−0.175	−1.7799	−0.0844	0.2689
Colombia	IGBC	min.	2.01%	Jan-16	0.1522	0.1678	−0.2795	−0.0572	0.0258	0.0794
Colombia	IGBC	max.	38.47%	Jan-12	0.511(**)	1.3126(**)	−0.9686	1.6203(*)	1.1996	−0.66(**)
Czech Republic	IPX	min.	8.63%	Nov-17	0.2273	0.2003	0.1382	−0.065	−0.5703	−0.02
Czech Republic	IPX	max.	76.14%	Oct-08	0.8546(**)	0.1008	−0.6502	0.3598	−0.231	−0.3354
Egypt	EGX30	min.	6.85%	June-14	0.1557	0.3858	0.0358	−0.7997	1.8975	−0.6212
Egypt	EGX30	max.	73.35%	Dec-10	1.1104(**)	0.6319	1.2351	2.0663(**)	1.5542	−0.9554(**)
Greece	ASE	min.	12.62%	Apr-19	−8.6363(*)	−13.0778	7.3631	1.1754	−11.7524	−4.0723
Greece	ASE	max.	78.31%	Nov-08	0.8758(**)	0.1913	−0.7895	0.2506	−0.2617	−0.8123(*)
Hungary	BUX	min.	26.49%	Feb-16	0.294	0.6244	0.4951	−0.9041	−1.5053	−0.0579
Hungary	BUX	max.	82.39%	Sep-12	0.6206(**)	0.1137	2.1934(**)	1.2777	−0.6809	−0.2521
India	SENSEX	min.	42.85%	Oct-16	0.7024(**)	−0.3516	−0.476	0.3484	−0.3366	0.2856
India	SENSEX	max.	82.83%	Sep-12	0.6924(**)	−0.1107	−0.5491	−0.6953	−0.3594	−0.2993
Indonesia	JCI	min.	23.76%	Sep-17	0.4606(**)	0.1921	−0.0481	1.233(*)	0.5191	−0.0278
Indonesia	JCI	max.	82.93%	June-12	0.8644(**)	0.5632	−0.671	−0.7321	−0.1225	0.2407
Malaysia	KLCI	min.	25.34%	Dec-15	0.3498(**)	0.05	−0.35	0.5139	0.6058	0.0053
Malaysia	KLCI	max.	68.47%	Feb-11	0.2796(**)	0.2182	0.6102	−0.091	−0.7801	0.0811
Mexico	IPC	min.	33.12%	Nov-15	0.2637(*)	−0.3994	0.4505	0.2929	0.525	−0.0227
Mexico	IPC	max.	70.72%	May-12	0.4629(**)	−0.5206	−0.1066	−0.5462	−0.7432	0.2522
Pakistan	KSE100	min.	3.92%	Sep-15	0.0827	0.2419	0.6247	0.6283	−0.1123	−0.0168
Pakistan	KSE100	max.	32.09%	Apr-11	0.3529	0.068	3.0669(**)	2.1575	0.0982	0.3259
Peru	SP-BVL	min.	24.36%	Aug-14	0.4846	0.5885	0.5166	0.4603	−0.6329	−0.5435
Peru	SP-BVL	max.	62.17%	Sep-10	1.181(**)	0.6366	0.82	−0.4538	0.7824	0.0149
Philippines	PSEI	min.	26.66%	Apr-08	0.4085(*)	0.7858(*)	−0.0597	0.4842	−0.7341	−0.3242
Philippines	PSEI	max.	67.80%	Nov-13	0.8609(**)	0.1499	−1.391(**)	−0.9028	0.2148	0.5713(**)
Poland	WSE	min.	25.19%	July-17	0.4699(**)	0.0354	0.0619	−0.2124	0.6386	0.0366
Poland	WSE	max.	73.44%	Aug-12	0.6929(**)	−0.3454	0.5764	1.167	−0.4267	−0.0099
Qatar	QSE	min.	3.37%	June-14	0.1243	0.3208	0.1745	−0.1817	0.3526	−0.0205
Qatar	QSE	max.	68.35%	July-11	0.7447(**)	−0.7697	0.1372	−0.5603	−0.55	−0.0722
Russia	MOEX	min.	4.68%	June-18	0.1406	−0.4453	−0.4683	−0.4982	0.1506	−0.1681
Russia	MOEX	max.	80.38%	Mar-13	0.5774(**)	−0.2774	1.0103(*)	−0.3439	−0.0115	−0.474(**)
Saudi Arabia	TASI	min.	5.81%	Mar-08	0.0093	−1.0672	0.0879	0.6243	0.4396	0.078
Saudi Arabia	TASI	max.	66.62%	Jan-12	0.7796(**)	0.4535	−0.9015	0.6082	−0.1187	0.0282
South Africa	JSE	min.	29.65%	Nov-19	0.4342(**)	−0.2278	−0.2771	0.0992	0.2915	0.0307
South Africa	JSE	max.	71.38%	Mar-12	0.666(**)	−0.3661	0.2699	0.8301	0.7142	−0.0246
South Korea	KOSPI	min.	52.97%	Dec-17	0.4737(**)	0.0749	0.19	0.4999	−0.379	0.0958
South Korea	KOSPI	max.	77.48%	Jan-12	0.6914(**)	−0.3226	0.9053	1.2511(*)	−0.0476	−0.019
Taiwan	TWSE	min.	45.58%	May-16	0.4679(**)	0.1349	0.1992	0.1441	−0.2683	0.1436
Taiwan	TWSE	max.	79.53%	Mar-12	0.9382(**)	0.4131	0.1665	0.9411	0.97(*)	−0.2518
Thailand	SET	min.	29.55%	Nov-17	0.3868(**)	−0.118	−0.0267	0.0164	−0.1706	−0.1114
Thailand	SET	max.	77.89%	Oct-11	0.6377(**)	0.5106	−0.622	−1.8971(**)	−0.734	0.5001(*)
Turkey	XU	min.	20.79%	May-15	0.5974	−0.6144	0.4483	0.514	1.4175	−0.0635
Turkey	XU	max.	65.73%	Aug-11	1.012(**)	0.7381	0.2788	2.0059(*)	0.3669	−0.4685
United Arab Emirates	ADX	min.	14.20%	Jan-18	0.2668	0.7331	0.1802	0.3387	0.4611	−0.3098
United Arab Emirates	ADX	max.	52.68%	Feb-12	0.5473(**)	0.6972	0.662	1.3717	−0.1939	0.3087

Note: (**) and (*) means statistically significant at 1% and 5% respectively.

3. Data

Unlike the empirical studies reviewed, portfolios and factors are not constructed in this empirical study, to ensure greater objectivity of the results. Therefore, while the monthly values of the risk factors and the risk-free rate are obtained from

Table 3
Weights of market and information portfolios and $beta_{SDF}$.

Country	Index	weights($Mkt - Rf$)	weights(SDF)	β_{SDF}
Argentina	MERVAL	1.93%	70.42%	0.8961
Brazil	BOVESPA	4.38%	−70.64%	0.2368
Chile	IPSA	5.09%	−14.38%	0.0136
China	Shanghai SE	2.53%	−9.66%	−0.2593
Colombia	IGBC	1.48%	24.38%	−0.3074
Czech Republic	IPX	4.19%	−45.96%	−0.1988
Egypt	EGX30	1.45%	−25.68%	0.8219
Greece	ASE	0.00%	49.40%	2.9256
Hungary	BUX	4.04%	28.31%	−0.4007
India	SENSEX	4.52%	−28.00%	−0.123
Indonesia	JCI	4.90%	18.35%	−0.4948
Malaysia	KLCI	7.38%	51.56%	−0.0758
Mexico	IPC	5.47%	−46.53%	0.0907
Pakistan	KSE100	1.24%	48.26%	−0.0422
Peru	SP-BVL	2.99%	−53.07%	−0.3261
Philippines	PSEI	4.51%	−8.06%	−0.1131
Poland	WSE	4.54%	−4.24%	−0.229
Qatar	QSE	3.21%	−15.11%	0.1126
Russia	MOEX	3.75%	12.34%	−0.5392
Saudi Arabia	TASI	3.41%	1.18%	−0.4357
South Africa	JSE	6.10%	64.36%	0.2265
South Korea	KOSPI	5.96%	10.29%	−0.6146
Taiwan	TWSE	5.71%	32.07%	−0.1944
Thailand	SET	5.03%	32.83%	−0.1787
Turkey	XU	3.01%	−1.39%	0.097
United Arab Emirates	ADX	3.19%	−21.06%	−0.2112
sum		100.00%	100.00%	

the French web database (http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html#International) for emerging equity markets , we use as the assets returns the monthly return of stock market indexes (from Bloomberg) for the countries considered to calculate risk factors of emerging equity markets in French web data. The period under analysis runs from January 2004 to December 2019, both inclusive.

Table 1 shows a descriptive statistical analysis of data.

From the results of Table 1, we observe that the mean values of the factors and the market indexes are similar, except in the case of Argentina, which is slightly higher. About the volatility, measured by the standard deviation of the series, we observe that except for the markets of Chile, Mexico and South Africa, the rest of indexes present values higher than the risk factors. Finally, regarding the tails of the distribution (kurtosis), we found that several markets (Greece, the Czech Republic, Indonesia, Pakistan, Peru, Thailand and the United Arab Emirates) show higher values than those of a Gaussian distribution.

4. Empircal results

Firstly, we run rolling (with previous 4 years or 48 monthly observations[2]) regression of excess returns for each market index on risk factors as expression-(1). For each market index, Table 2 only show two estimation, those of higher and lower goodness of fit.

Note that excess market return is the risk factor more significant and the rest of risk factors are only significant for 7 indexes (RMW), 6 indexes (HML and WML), 3 indexes (SMB) and 0 indexes (CMA). Additionally, the maximum, minimum, average values of R^2 are 87.27%, 2.01% and 46.51%, respectively. Therefore, six-factors model shows, in general, a low accurate of asset returns.

As a consequence of the previous results, we estimate SDF. Table 3 show weights of each market index in information-SDF portfolio (see expression-(6)) and sensitivity ($beta$ for SDF) of excess return of each index to information-SDF portfolio return. Additionally, for comparative reason, we include market portfolio ($Mkt - Rf$) weights applying the same estimation methodology.

Note in Table-3 that the highest weights (over 40% in absolute value) of equity markets are from Argentina (long position or +), Brazil (short position or −), Czech Republic (short), Greece (long), Malaysia (long), Mexico (short), Pakistan (long), Peru (short) and South Africa (long). Regarding the market portfolio weights, we observe that all the positions are long, which implies that the information of the correlation sign between emerging markets is not considered, in addition the rank of the size of the weights is not similar (in absolute value) to the estimate for the information-SDF portfolio.

Now, in Table 4, we compare statistically excess returns of the information-SDF portfolio and the market portfolio ($Mkt - Rf$).

[2] Estimates have also been made with 3 and 5 years of previous data and the results are similar. These values are available upon request to the authors.

Table 4
Statistics of information-SDF and market portfolios.

Statistics	Return SDF	Mkt-Rf
Mean	3.99%	0.41%
Median	3.96%	0.64%
min	2.05%	−27.29%
Max	5.69%	17.98%
Std. Dev.	0.0106	0.0614
Skw.	−0.0709	−0.558
Kurt.	−1.296	2.9963
CV (Mean/Std. Dev.)	3.7645	0.0675

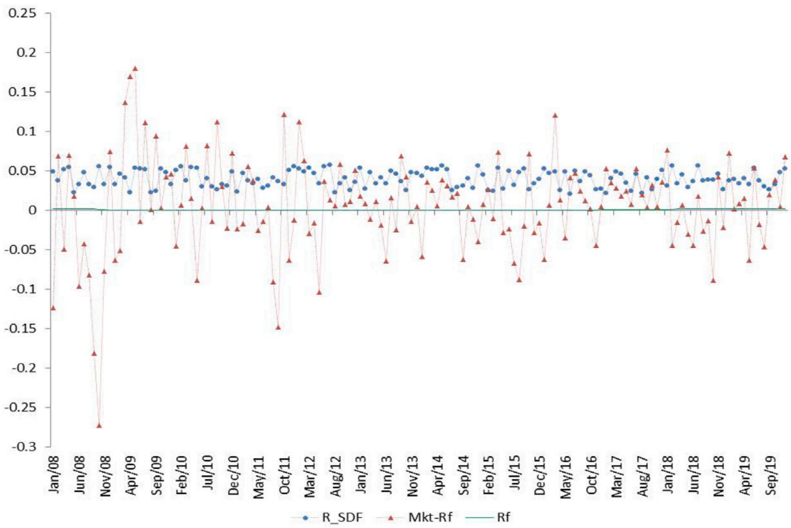

Fig. 1. Monthly returns of information-SDF and market portfolios.

From Table 4, we note that information-SDF portfolio shows higher mean and median returns than market portfolio and, lower standard deviation, skewness and kurtosis. Therefore, information-SDF portfolio has higher return per unit of risk (coefficient of variation, CV). Besides, Fig. 1 show monthly returns of information-SDF, and market portfolios and risk-free rate.

From Fig. 1, we observe that market portfolio is more volatile than information-SDF portfolio and, the return of the latter, unlike the market portfolio, never takes negative values, which is the necessary and sufficient condition for no arbitrage. Besides, there are no cases in which the information-SDF portfolio return is lower than Rf with an average difference about 3.94%.

Now, we study alpha-anomalies for factorial models and information-SDF portfolio, i.e., we test for each i-index whether $\alpha_{0,i} \neq 0$.

From Table 5 results, we accept, for information-SDF portfolio, the hypothesis $\alpha_{0,i} = 0$ and for all indexes; while for factorial models we reject it, since the indexes of Argentina, Czech Republic, India, Poland, Russia and United Emirates Arab show a statistically significant intercept ($\alpha_{0,i} \neq 0$). Therefore, information-SDF portfolio does not show $alpha$-anomaly, however, factorial models present this anomaly.

Table 6 show risk premiums estimates, as Fama and MacBeth (1973), for linear model including different risk factors and, for information-SDF portfolio.

The results of Table 6 indicate that only HML factor explains (parameter is statistically significant) the risk premium of emerging equity markets or, if this factor is excluded of factorial model then, SMB premium is only significant regressor. For these factorial models, the goodness of fit (R^2) is between 30%–59%, instead, information-SDF portfolio show a significant premium (0.83%) and an explanatory level of R^2=63%. In short, only one factor (SDF) is more explanatory than a six-factors model, and then, this is our first contribution to empirical financial studies about emerging equity markets.

Now, we estimate expression-(7) to analyze whether some risk factor explains the behavior of information-SDF portfolio.

From Table 7, note that estimation is not statistically significant for any risk factor and, HML factor has the highest R^2 (4.22%). Thus, our second contribution is that information-SDF identifies a novel source of risk not captured by usual risk factors.

Finally, since we have found empirical evidence on the sensitivity of market indexes to the HML factor, although its explanatory capacity is lower than SDF and, given that, from the results of Table 7, we verify that HML and SDF are not correlated then, a question arises about the effects of both information sets. About that Fig. 2 shows average sensitivity ($beta$) of each emerging market index to HML and SDF portfolios. Note that $beta_{SDF}$ and $beta_{HML}$ are similar, except to KSE-100 (Pakistan), WSE (Poland), KOSPI (South Korea) and ADX (United Arab Emirates) then, HML portfolio seems a sensitivity measure at risk, i.e., as Ali et al. (2003), we find that the book-to-market ratio (HML) effect is greater for stocks with higher idiosyncratic return volatility (as our sample of emerging stock markets).

Table 5
$Alpha$ values for factorial models and information-SDF portfolio.

Country	Index	SDF	$Mkt-Rf$	$Mkt-Rf$ SMB	$Mkt-Rf$ SMB HML	$Mkt-Rf$ SMB HML RMW	$Mkt-Rf$ SMB HML RMW CMA	$Mkt-Rf$ SMB HML RMW CMA WML
Argentina	MERVAL	0.0032	0.0221(**)	0.0216(**)	0.0152(*)	0.0177(*)	0.0184(*)	0.0186(*)
Brazil	BOVESPA	0.0105	0.0023	0.0039	−0.0016	0.0016	0.0009	0.0014
Chile	IPSA	0.0029	0.0016	0.0014	0.0006	−0.0013	−0.0024	−0.002
China	Shanghai SE	0.009	−0.004	−0.0045	−0.0057	−0.0073	−0.0058	−0.0061
Colombia	IGBC	−0.0087	0.0029	0.0007	0.0025	0.0003	−0.0001	0.0006
Czech Republic	IPX	0.0059	−0.0048(*)	−0.0053(*)	−0.0055(*)	−0.0094(*)	−0.0074(*)	−0.0074(*)
Egypt	EGX30	−0.0027	0.0034	0.0003	−0.0025	0.0042	0.006	0.0067
Greece	ASE	−0.0088	0.0291	0.0427	0.0276	0.0307	0.0636	0.0644
Hungary	BUX	0.0022	0.0024	0.0012	−0.0015	−0.0014	0.0042	0.0044
India	SENSEX	0.0011	0.0031(*)	0.0031(*)	0.005(*)	0.0069(**)	0.0112(**)	0.0115(**)
Indonesia	JCI	0.0027	0.0041	0.0025	0.0034	0.0046	0.0051	0.0049
Malaysia	KLCI	0.0038	−0.0008	−0.0016	−0.0015	−0.003	−0.0031	−0.003
Mexico	IPC	−0.0004	0.0011	0.0026	0.0022	0.0026	0.0026	0.0028
Pakistan	KSE100	0.0011	0.0083	0.0088	0.0055	−0.0068	−0.0071	−0.0075
Peru	SP-BVL	0.0017	0.0001	−0.0002	−0.0033	0.0008	0.0024	0.0029
Philippines	PSEI	0.0011	0.004	0.0032	0.0045	0.0026	0.0028	0.0024
Poland	WSE	0.007	−0.0049(*)	−0.0049(*)	−0.0065(*)	−0.0121(**)	−0.0111(**)	−0.0109(**)
Qatar	QSE	−0.0021	−0.0003	−0.0006	−0.0026	−0.0007	0	0.0005
Russia	MOEX	0.0027	0.0019(*)	0.0016(*)	0.0017(*)	0.0048(*)	0.0088(*)	0.0088(*)
Saudi Arabia	TASI	0.0017	−0.0029	−0.0054	−0.0049	−0.0058	−0.0067	−0.0064
South Africa	JSE	−0.0039	0.0031	0.0036	0.0038	0.0021	0.0005	0.0003
South Korea	KOSPI	0.0026	−0.0009(*)	−0.0006(**)	0.0001	−0.0067(*)	−0.0064(*)	−0.0065(*)
Taiwan	TWSE	0.0011	0.0004	−0.0006	0.0003	−0.0001	0.0001	0.0002
Thailand	SET	0.0013	0.0025	0.0014	0.0015	0.0055	0.0055	0.0052
Turkey	XU	0.0036	0.0042	0.0041	0.0046	−0.0007	−0.0017	−0.0012
United Arab Emirates	ADX	0.001	−0.0049(*)	−0.0021(*)	−0.0031(*)	−0.0063(*)	−0.0068(*)	−0.0073(*)

Note: (**) and (*) means statistically significant at 1% and 5% respectively.

Table 6
Risk premiums estimated.

Premium	const	$Mkt-Rf$	SMB	HML	RMW	CMA	WML	SDF	R^2
λ	0.0015	0.0036	−0.001	0.006	−0.0026	0.0008	−0.0021		59.08%
t-value	0.3688	0.6445	−0.3442	2.4413	−1.1163	0.3017	−0.382		
λ	0.0018	0.0033	−0.0011	0.006	−0.0028	0.0009			58.76%
t-value	0.4817	0.6114	−0.3758	2.5204	−1.2368	0.3503			
λ	0.001	0.0044	−0.0007	0.0057	−0.0024				58.51%
t-value	0.3438	1.0082	−0.2641	2.6437	−1.2629				
λ	0.0007	0.0045	−0.0011	0.0057					55.36%
t-value	0.2398	1.0145	−0.4536	2.6241					
λ	0.0054	0.0003	−0.0049						41.39%
t-value	2.1411	0.0616	−2.0876						
λ	0.0095	−0.0081							30.28%
t-value	5.4846	−3.2286							
λ	0.0053							0.0083	63.55%
t-value	1.9681							6.4681	
λ	0.0029	0.0036		0.0063					54.94%
t-value	3.3144	0.9236		3.548					
λ	0.0033			0.0049					53.27%
t-value	3.0829			5.2307					

Note: t-value are estimated with heteroscedasticity and autocorrelation robust standard errors.

5. Conclusions

Financial literature shows that factorial asset pricing models are biased and present asset pricing anomalies. Also, the revised empirical research about emerging markets found these drawbacks.

Table 7
Regression results of information-SDF portfolio on risk factors.

Factors	Parameter	t-value	R^2
Mkt-Rf	−0.0022	−0.1494	0.02%
SMB	−0.0742	−1.1712	0.96%
HML	−0.0031	−1.5583	4.22%
RMW	0.0093	0.1157	0.01%
CMA	0.0665	1.0799	0.81%
WML	−0.0371	−1.1974	1.00%

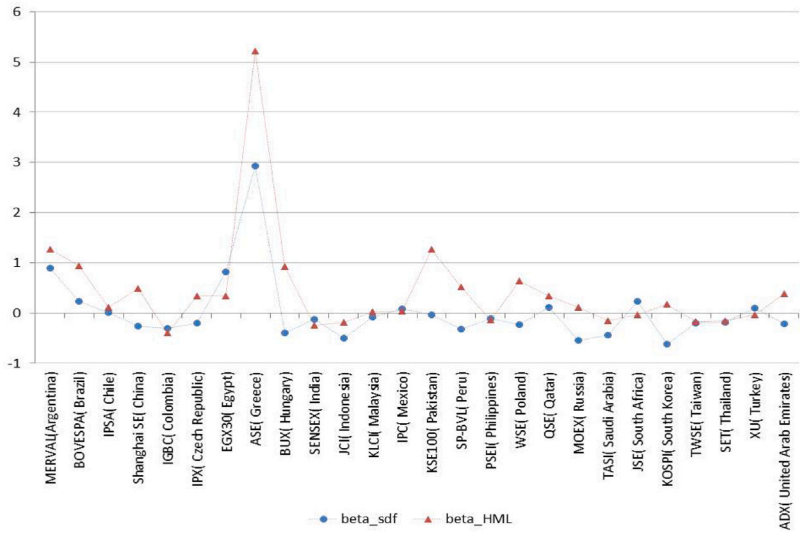

Fig. 2. Average *betas* of information-SDF portfolio and HML factor.

In this context, the first contribution of this study is to apply on emerging equity markets a novel methodology (Gosh et al., 2017) to estimate SDF and subsequent portfolio of information. The advantage of this approach is that it avoids assuming both the underlying pricing model and the risk factors, therefore it is a non-parametric method.

Looking for the impartiality of our results, the all sample is obtained externally. We obtain the Fama–French (monthly) factors and the momentum factor for emerging markets from French web data. Likewise, and for the same sample period (January-2004 to December-2019), we use as assets to price the indexes (26) of the same emerging markets used by French web data to estimate the factors.

The results show that the goodness of fit for the information-SDF portfolio is higher than any of the factor models. Furthermore, we find that the weights of emerging markets are different from those of the market portfolio, which shows that the proposed SDF methodology uses new sources of information to reduce anomalies. Notice that only the variable HML (book-to-price ratio) provides relevant information for the valuation of emerging assets, although not as a risk factor, but as a measure of sensitivity at risk. Thus, the theoretical contribution of this empirical study is that the usual factors used in asset pricing in developed markets show less explanatory power than non-parametric models. Additionally, the HML factor in emerging markets is an indicator of the risk sensitivity of assets.

The empirical evidence found is relevant to the extent that they can help managers, investors and researchers from emerging markets to use new sources of information in the valuation of assets. Therefore, our empirical evidence has relevant practical implications since the use of non-parametric models (SDF) is more consistent in the asset pricing in emerging market and also to analyze the variability of the risk sensitivity of emerging market assets as a function of book-to-price ratio.

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