Business and Economics Journal

LP Lopes Fávero et al.,, Bus Eco J 2014, 5:2
DOI: 10.4172/2151-6219.100088

Research Article Open Access

Propensity for Growth of Stock Prices in Emerging Markets: A Logit Panel Approach

Luiz Paulo Lopes Fávero[1*], José Elias Feres de Almeida[2] and RenataTurola Takamatsu[3]

[1]*School of Economics, Business and Accounting, University of São Paulo, Av. Prof. Luciano Gualberto, 908, FEA 3, sala 211, Cidade Universitária, São Paulo (SP), Brazil*

[2]*Center for Law and Economics, Federal University of Espírito Santo, Av. Fernando Ferrari, 514, CCJE,ed-VI, sala 636, Campus Universitário, Goiabeiras, Vitória (ES), Brazil*

[3]*School of Economics, UniversityofMinas Gerais, Av. Antônio Carlos, 6627, sala 2042, Pampulha, Belo Horizonte (MG), Brazil*

[*]**Corresponding author:** Luiz Paulo Lopes Favero, School of Economics, Business and Accounting, University of São Paulo, Av. Prof. Luciano Gualberto, 908, FEA 3, sala 211, Cidade Universitária, São Paulo (SP), CEP 05508-900, Brazil, Tel: (55 11) 3091-5820; Fax: (55 11) 3091-5820; E-mail: lpfavero@usp.br

Received date: December 9, 2013, **Accepted date:** March 28, 2014, **Publication date:** May 12, 2014

Abstract

We investigate the effects of financial variables to increase the propensity for growth of capital markets stock indexes in60 emerging markets. We draw our sample from Compustat Global during a 257-month period (1986-2007) for a total of 9,759 observations. Our data indicate that price-to-book and turnover ratio leads to positive monthly returns of stock indexes, while evidence for traded volume is weak. However, market capitalization has a negative influence and reduces the probability of positive returns, suggesting that price pressure for transitory returns exists in these markets. This paper contributes to the financial market literature about emerging markets. It also provides useful information to regulators, investors, and practitioners for developing policies and strategies to improve the development of financial markets.

Keywords: Logit panel; Random effects; Stock markets; Emerging markets

Introduction

The relation between stock market indexes and stock market and economic characteristics in developed countries is well documented. However, studies about the influence of financial market variables on stock indexes in developing countries, from a time perspective and the measurement of positive returns, remain scarce [1].

Financial development is necessary and useful for the economic development of a nation, which provides feedback to the development of the stock market itself [2-5]. According to Roe and Siegel [5], many factors can explain the differences in financial market development around the world, especially in emerging countries. In addition to the characteristics associated with the companies and organizations themselves, many market variables can interfere in the evolution of financial market indicators over time. But what induces distinctive behaviors in the monthly evolution of one country's indicators in comparison with those of others? Alexander and Luigi [6], among others, suggest that the distinctive behaviors arise from a combination of factors related to legal, economic, and social aspects; commercial opportunities, and conditions of active companies. According to Steven and Kevin [7], political factors also play a role.

This study investigates the effects of financial market variables on the probability of a positive monthly return on stock indexes in 60 emerging countries during 257 months, between 1986 and 2007. A total of 9,759 observations are obtained from the Compustat Global database. In contrast to some previous studies (see section 1), we use Logit panel data models to measure positive returns over time from different observations, instead of using models to preview the return metric itself. We exclude data from 2008 to 2012 to reduce the effects of the international financial crisis on the results.

According to Charles and Nicholas [8], capital market development is an increasingly fundamental aspect in the development of the entire financial market in emerging countries. It allows companies to obtain capital in more open, transparent markets with faster and more efficient transactions, thus facilitating investment activities and enhancing a more sustained growth of production means. According to Tobin [9] and Von Furstenberg [10], stock market activity is positively correlated with investment.

Our results show that financial market variables such as price-to-book and turnover ratios increase the probability of positive returns. In other words, growth opportunities and liquidity in emerging markets determine an increased propensity for positive stock returns. In general, the negotiated stock volume is not significant, a condition that can reflect the low liquidity level of capital markets in some emerging countries.

This paper supports the development of public policies by international entities and in each emerging country to stimulate capital market development.

Background

Prior research analyzes emerging markets and their financial development by taking into account their fundamentals and how macroeconomics and/or microstructure variables behave due to financial liberalization or by integrating international financial development [11-15].

For example, Claessens et al. [11] demonstrate that size, trading volume, dividends yield, and price-to-book ratio affect returns differently among developed countries as well as emerging markets.

Fávero and Almeida [16] provide evidence that price-to-book, dividends yield, and turnover influence stock indexes in emerging markets; moreover, country effect changes growth rates of stock indexes in the capital markets.

While the literature focuses on returns and assumes normal distributions of log returns, returns are not normally distributed in emerging markets [12]. In contrast to previous studies, we analyze the probability of the content of financial market variables to generate positive returns (dummy variable for positive returns), and we expect to capture different properties of financial variables.

We do not control market segmentation or integration in this paper; we instead focus on local positive returns because no conclusive evidence exists in the literature about factors that affect returns in emerging markets.

Our first hypothesis relates to dividend yields. This variable is a proxy for cost of capital; however, dividend yields decrease when the cost of capital decreases or when growth opportunities increase in markets [13]. We expect dividend yields to be negative when the propensity for positive returns is greater.

In this context, growth opportunities are related to a reduction in dividend yields; according to Geert et al [14], "lower dividend yield may also reflect an improvement in growth opportunities". To control this factor, we consider market-to-book ratio as a proxy for growth opportunities, and we expect that high growth opportunities increase the probability of positive returns, since market agents recognize future prospects faster than accounting systems due to accounting standards (e.g., conservative practices).

Size is used as a proxy for market liquidity and the amount of information available [13]. Usually, researchers use market capitalization to measure size. We similarly expect that size impacts the probability of positive returns, taking into account that bigger markets attract more investors because there is more information available for economic decision-making. However, Geert and Campbell [14] argue that price pressure is related to speculation, and it is negatively related to returns, but if "the price increase is permanent, it may reflect a long-lasting decrease in the cost of equity capital associated with the risk sharing benefits of capital market openings in emerging markets".

Time is a factor that affects emerging markets. According to Geert and Campbell [14] "history is important in studying these markets", and using the number of days of market operations is a way to control for financial market development during the period that we investigate in this paper. However, there is no clear expectation for coefficient signal direction.

Liquidity in asset pricing literature is usually measured by turnover because this variable reflects information about stocks traded. We expect that a high turnover rate of stocks increases the probability of positive returns. In the same way, we expect that the number of stocks negotiated increases the probability of positive returns, since more information is available in the market, and also contributes to increase liquidity.

The modeling: binary dependent variable panel data

The use of panel data models to assess financial market returns is increasingly common and represents new challenges to formulate problems with a view to assessing performance assessment. These models permit estimating the relation between performance and different market variables over time.

Many different models exist that can be used for panel data in accounting and finance [17]. The basic distinction among them, according to Greene [18], is the existence of fixed or random effects. The term "fixed effects" transmits a mistaken idea about the modeling because the effects at the individual (in this case country) level are random in all cases. Thus, according to Cameron and Trivedi [19], an additional complication in the fixed effect models is that the regressor variables are correlated with effects at the individual level; therefore, a consistent estimation of model parameters demands elimination of or control for fixed effects. Hence, a model that takes into account the individual specific effects for a dependent variable, y_{it}, specifies that:

$y_{it}=\beta_{0i}+X'_{it}\,\beta_1$ (1)

Where xit is a regressor variable, $\beta_{0i}$is the individual specific random effect, and εit represents the idiosyncratic error.

A panel data model in which the dependent variable is represented by a dummy y_{it} with x_{it} regressor, in which i indicates the individual and t the period, can be specified as follows, according to Cameron and Trivedi [19]:

$f\left(y_{it}\middle|\alpha_i,X_{it}\right)=f\left(y_{it},\alpha_i+X'_{it}\beta,\gamma\right)$, t=1, ..., Ti, i=1, ..., N (2)Where γ represents the parameters of an additive model, as variance parameters, and αi indicates the effect of each individual.

In this paper, we study models with different estimators. The model with a pooled logit estimator is actually a cross-section of a traditional model, represented as follows:

$\Pr(y_{it}=1|X_{it})=(X'_{it}\,\beta)$ (3)

Where (z)=ez/(1+ez). We use estimation with clustered robust errors in this paper, so as to correct occasional correlations in error terms over time for a given individual [20].

Another estimator that we use is the PA logit estimator, in which the correlations are assumed to be the same, independent of how many periods the observations are distant.

$\rho_{ts}=\mathrm{corr}\{[y_{it}-\Lambda(X'_{it}\beta)][y_{is}-\Lambda(X'_{is}\beta)]\}$, $s \neq t$ (4)This model is adequate for the data in this paper because there is little variation in the correlations between the dummy variable and its lags (Table 4). According to Cameron and Trivedi [19], co-variances can vary among individuals and over time because, given that$\mathrm{Var}\left(y_{it}|X_{it}\right)=\Lambda_{it}(1-\Lambda_{it})$, covariance corresponds to$\alpha\sqrt{\Lambda_{it}(1-\Lambda_{it}).\Lambda_{is}(1-\Lambda_{is})}$.

Also according to Cameron and Trivedi [19], the logit model with individual effects specifies that:

$\Pr(y_{it}=1|X_{it},\beta,\alpha_i)=\Lambda(\alpha_i+X'_{it}\beta)$ (5)

Where α_i can be a fixed effect or a random effect.

Logistic random effects regression models specifies that$\alpha_i\sim N\left(0,\sigma^2_\alpha\right)$. Hence, the probability density function for the i-th observation is $f\left(y_{it},\dots,y_{iT}\right)=\int\left\{\prod_{t=1}^{T}\Lambda\left(\alpha_i+X'_{it}\beta\right)^{y_{it}}\left[1-\Lambda\left(\alpha_i+X'_{it}\beta\right)\right]^{1-y_{it}}\right\}g|\sigma^2)d\alpha_i$(6)

Where g (αi|σ2) is the density. As, in this case, Pr(yit=1| Xit,β)1(X'itβ), the parameters of the random effects model are not comparable with those obtained based on the pooled logit and PA logit models.

Citation: Lopes Fávero LP, de Almeida JEF,Takamatsu RT (2014) Propensity for Growth of Stock Prices in Emerging Markets: A Logit Panel Approach. Bus Eco J 5: 88. doi:10.4172/2151-6219.100088

In the random effects model, α_i has to be correlated with the co-variables in the model. Thus, the conditional maximum likelihood estimation method eliminates the term α_i when the equation is estimated. For two time periods, given that the condition is $y_{i1}+y_{i2}=1$:

$$\Pr\left(yi1=0,yi2=1|yi1+yi2=1\right)=\frac{\Pr\left(yi1=0,yi2=1\right)}{\Pr\left(yi1=0,yi2=1\right)+\Pr\left(yi1=1,yi2=0\right)}$$

(7)Because Pr(yi1=0, yi2=1)=Pr(yi1=0).Pr(yi2=1) and yi1 and yi2 are assumed to be independent, with αi and xit given, according to Cameron and Trivedi [19], the logit model appears as follows:

$$\Pr\left(yi1=0,yi2=1\right)=\frac{1}{1+e^{\left(\alpha i+X_{i1}^{'}\beta\right)}}.\frac{e^{\left(\alpha i+X_{i2}^{'}\beta\right)}}{1+e^{\left(\alpha i+X_{i2}^{'}\beta\right)}}\quad(8)$$

Similarly:

$$\Pr\left(yi1=1,yi2=0\right)=\frac{e^{\left(\alpha i+X_{i2}^{'}\beta\right)}}{1+e^{\left(\alpha i+X_{i2}^{'}\beta\right)}}.\frac{1}{1+e^{\left(\alpha i+X_{i1}^{'}\beta\right)}}\quad(9)$$

And, therefore:

$$\Pr\left(yi1=0,yi2=1|yi1+yi2=1\right)=\frac{1}{1+e^{\left(\alpha i+X_{i1}^{'}\beta\right)}}.\frac{e^{\left(\alpha i+X_{i2}^{'}\beta\right)}}{1+e^{\left(\alpha i+X_{i2}^{'}\beta\right)}}$$

$$\Pr\left(yi1=0,yi2=1|\ yi1+yi2=1\right)=\frac{e^{\left(X_{i2}^{'}\beta\right)}}{e^{\left(X_{i1}^{'}\beta\right)}+e^{\left(X_{i2}^{'}\beta\right)}}$$

$$\Pr\left(yi1=0,yi2=1|\ yi1+yi2=1\right)=\frac{e^{\left(Xi2-Xi1\right)^{'}\beta}}{1+e^{\left(Xi2-Xi1\right)^{'}\beta}}\quad(10)$$

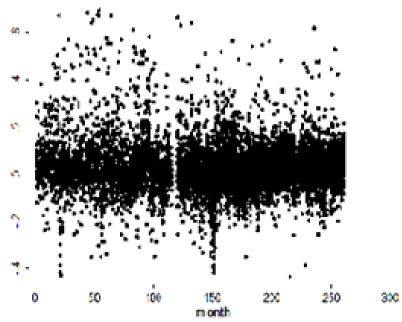
Also according to Cameron and Trivedi [19], αi can be eliminated, conditioning $\Sigma_{t=1}^{T}yit=1,\Sigma_{t=1}^{T}yit=2,\ldots,\ \Sigma_{t=1}^{T}yit=T-1$. This generates a loss of observations in which yit= 0 for any t or yit= 1 for any T.In this paper, we present the results of the pooled logit and PA logit models with random and fixed effects, with a view to better understanding the different types of estimators, as well as obtaining an adequate model to explain positive stock index return events in emerging countries.

Data, Variables, and the Proposed Model

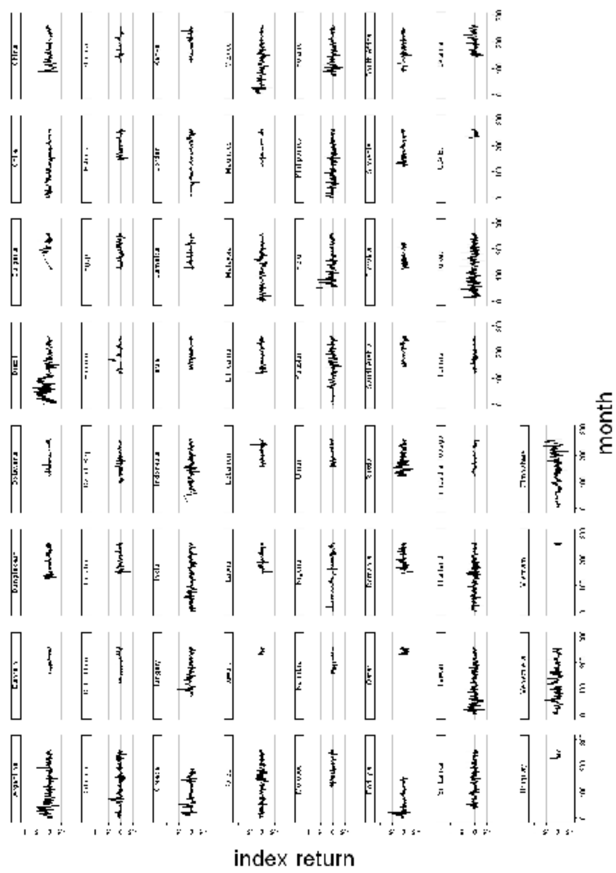
The dependent variable: monthly return of the main stock index

Using the Compustat Global database, we collect the evolution in each emerging country's monthly stock indexes and the characteristics of each stock market. We extract the data from all emerging country data sets available in the database for the period between 1986 and 2007; that is, we survey data for 60 countries, for a period of 257 months, totaling 9,759 observations.

Graph 1presents the performance variable under analysis (the monthly return of the main stock index in each of the 60 emerging countries), and each point represents the stock index return of a given country within a given month. Graph 2 presents these returns over time for each emerging country.



Graph 1: Stock index returns in emerging countries over time



Graph 2: Stock index returns over time per country

As our main goal is to investigate the effects of capital market characteristics on the probability of positive monthly stock index returns in emerging countries over time, we create a dummy variable that corresponds to 1 when the monthly index return in a given country for a specific month is positive, and 0 when negative. Panel A in Table 1 shows the number of negative and positive monthly returns for the general sample across the study period, and panel B presents the number of events per country.

Panel A: Total Number of Positive and Negative Monthly Stock Index Returns									
Dummy variable			**Number of Events**				**Percentage**		
0 (Negative Monthly Return)			3,982				40.8		
1 (Positive Monthly Return)			5,777				59.2		
Total			9,759				100		
Panel B: Positive and Negative Monthly Stock Index Returns per Country									
	Dummy variable					**Dummy variable**			
Country	0	1		Total	País	0		1	Total
Argentina	102	148		250	Mauritius	55		86	141
Bahrain	43	60		103	Mexico	89		167	256
Bangladesh	67	72		139	Morocco	58		81	139
Botswana	40	101		141	Namibia	47		51	98
Brazil	83	162		245	Nigeria	77		179	256
Bulgaria	27	46		73	Oman	43		57	100
Chile	105	152		257	Pakistan	96		157	253
China	79	93		172	Peru	69		135	204
Colombia	95	161		256	Philippines	113		143	256
Cote d'Ivoire	61	79		140	Poland	72		113	185
Croatia	45	70		115	Portugal	74		79	153
Czech Rep	68	93		161	Qatar	16		17	33
Ecuador	41	86		127	Romania	41		70	111
Egypt	64	76		140	Russia	47		91	138
Estonia	47	70		117	Saudi Arabia	45		72	117
Ghana	43	98		141	Slovakia	49		56	105
Greece	82	94		176	Slovenia	57		83	140
Hungary	68	118		186	South Africa	65		109	174
India	105	149		254	Sri Lanka	98		122	220
Indonesia	92	118		210	Taiwan	114		143	257
Israel	48	74		122	Thailand	112		144	256
Jamaica	61	80		141	Trin. & Tobago	43		91	134
Jordan	125	127		252	Tunisia	68		73	141
Kenya	74	67		141	Turkey	99		144	243
Korea	124	133		257	U.A.E.	19		14	33
Kuwait	9	24		33	Ukraine	48		69	117
Latvia	48	67		115	Uruguay	12		24	36
Lebanon	52	50		102	Venezuela	108		140	248

Lithuania	64	75		139	Vietnam	4		5	9
Malaysia	105	152		257	Zimbabwe	77		167	244

Table 1: Distribution of Positive and Negative Returns in the Sample

As shown in Table 2, persistence between one period and the other is considerable; that is, 65% of stock indexes with positive returns in a given month also present this behavior in the subsequent month.

	Dummy variable		Total
Dummy variable	0	1	
0	49.40	50.60	100.00
1	34.97	65.03	100.00
Total	40.87	59.13	100.00

Table 2: Month-to-Month Transition in the Existence of Positive Returns

Obs.: Percentage values.

On the other hand, according to Table 3, little variation exists in the correlations between the dummy variable and its lags, which supports the choice of the logit panel data estimator, as discussed in a later section.

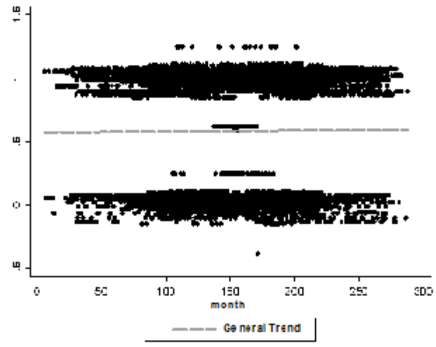
	Dummy variable	Dummy variable 1st Lag	Dummy variable 2nd Lag
Dummy variable	1.000		
1st Lag	0.1434	1.000	
2nd Lag	0.0545	0.1411	1.000

Table 3: Correlations between Dummy Variable and Lags

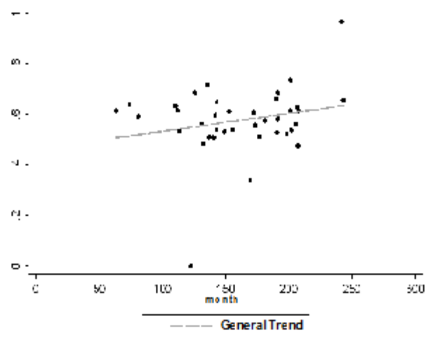
Graph 3 presents the variation in the dummy variable, corresponding to the monthly return of each stock index over time for each country; that is, it shows the deviations of this variable from each country's individual mean index (within variation). In addition, to illustrate the distribution of the dependent variable used in the models, Graph 4 presents the variation between countries; that is, it shows the deviations of this variable from the general mean index for each moment in time (between variation).

Independent variables

According to Cameron and Trivedi [19], panel data models can permit an endogenous regressor, due to the existence of correlation with an error component that does not vary over time (fixed events), or they can assume that the regressor variables are totally exogenous (random effects). We consider both estimators in this paper.



Graph 3: Deviations of Dummy Variable from Each Country's Mean Index over Time



Graph 4: Deviations of Dummy Variable from General Mean Index for Each Period

After elaborating the initial diagnosis, we do not expect a trend towards the existence of idiosyncratic variables in the sample, which could result from systematic behaviors of stock indexes among countries over time. In other words, we expect that relevant market variables exist for the occurrence of positive monthly stock market returns over time, which justifies the use of logit panel data models.

In this research, we adopt logit panel data models because some independent variables (capital market variables) can vary less over time than others, while others can vary even less among countries. These variables, which correspond to the regressors of the logit panel data models, are from this same database and are displayed in Chart 1.

Stock Market Variables (Regressors in Panel Data Models)	
dummyrent	Dummy corresponding to the monthly stock index return dummyrent=1 (monthly return ≥ 0)

Citation: Lopes Fávero LP, de Almeida JEF,Takamatsu RT (2014) Propensity for Growth of Stock Prices in Emerging Markets: A Logit Panel Approach. Bus Eco J 5: 88. doi:10.4172/2151-6219.100088

	dummyrent=0 (monthly return < 0)
lnyield	Natural logarithm of market dividends
lnp_bv	Natural logarithm of price/book value relation in the market
lnvtrdus	Natural logarithm of market negotiated value in million dollars
lntover	Natural logarithm of market turnover rate
lnnush	Natural logarithm of number of market negotiated stocks, in million
days	Number of days with market operations

Chart 1: Variable Definition for Logit Panel Data Models

Variance decomposition and the proposed model

The regressor variables can vary simultaneously over time and between individuals. Variance over time or for a given individual is known as within variance, while variance between individuals is called between variance. According to Wooldridge [21], in the fixed effects model, the coefficient of a regressor with low within variation will be estimated imprecisely and will not be identified if within variance is absent. Hence, it is fundamental to distinguish between these variations to define the best panel data model.

The total variation of observations for a regressor x around the general mean $\overline{X}=1/\Sigma_i T_i \Sigma_i \Sigma_t X_{it}$ in the data set can be decomposed into the sum of within variation over time for each individual around $\overline{X}_i=1/T\Sigma_t X_{it}$ and variation between individuals (for $\overline{X}_i$ around $\overline{X}$). According to Cameron and Trivedi [19]:Within variance: $S_{XW}^2=\frac{1}{\Sigma_i T_i-1}\Sigma_i\Sigma_t\left(X_{it}-\overline{X}_i+\overline{X}\right)^2$

Between variance: $S_{XB}^2=\frac{1}{N-1}\Sigma_i\left(\overline{X}_i-\overline{X}\right)^2$

Overall variance: $S_{XO}^2=\frac{1}{\Sigma_i T_i-1}\Sigma_i\Sigma_t\left(X_{it}-\overline{X}\right)^2$

The notations N and $\Sigma_i T_i$ correspond to the number of individuals and the total number of observations over time, respectively.

Table 4 presents the variance decomposition for each of the regressors presented in Chart 1, as well as for the dependent variable.

Variable	Decomposition	Mean	Standard Deviation	Minimum	Maximum	Observations
Country	overall					N.T=9,759
	between					N=60
	within		0.000			
Month	overall		68.753	1.00	261.00	N.T=9,759
	between		39.062	78.08	257.00	N=60
	within		59.967	25.87	293.66	
dummyrent	overall	0.591	0.491	0.00	1.00	N.T=9,759
	between		0.062	0.42	0.73	N=60
	within		0.488	-0.14	1.17	
Lnyield	overall	0.731	1.371	-4.60	7.19	N.T=6,424
	between		1.135	-3.21	2.09	N=45
	within		0.943	-4.51	5.82	
lnp_bv	overall	0.620	0.748	-4.60	5.94	N.T=6,819
	between		0.551	-0.97	1.86	N=52
	within		0.600	-4.25	5.69	
lnvtrdus	overall	5.300	3.014	-4.60	13.71	N.T=9,754
	between		2.735	-0.94	10.53	N=60
	within		1.423	-2.68	11.01	
Lntover	overall	0.434	1.473	-4.61	4.36	N.T=9,625
	between		1.275	-2.58	2.95	N=60
	within		0.823	-4.60	3.68	

Lnnush	overall	5.098	3.753	-7.68	16.38	N.T=9,710
	between		3.268	-2.62	12.93	N=60
	within		1.889	-6.63	14.13	
Days	overall	20.634	1.531	16.00	23.00	N.T=9,720
	between		0.378	19.50	21.50	N=60
	within		1.488	15.32	24.13	

Table 4: Panel Statistics and Within and Between Variance Decomposition

As shown in Table 4, the country obviously does not vary over time, and it's within variation is equal to zero. On the other hand, the time variable (month) does not vary between individuals because this is an unbalanced panel. Thus, it's between variation does not equal zero but is relatively smaller than its within variation. For most regressor, the between variation is larger than the within variation, but it cannot be affirmed yet that the within estimation will result in less efficiency because the proportion between the within and between variances for each variable differs and the statistical significances of each in the models is not known yet. Nevertheless, Table 4 provides further foundations to adopt panel data models and apply different estimators. The columns "Minimum" and "Maximum" present, respectively, the minimum and maximum values of xit for the line overall, $\overline{X}_i$for the line between and $\left(X_{it}-\overline{X}_i+\overline{X}\right)$ for the line within.

As discussed in section 2, we will elaborate four panel data models, with different considerations about the estimators. The general model to be adopted complies with the following:

$\Pr\left(\text{dummyrent}_{it}=1 \middle| X_{it}\right)=\frac{e^Z}{1+e^Z}$, in which:Z=α+β1. (lnyield)+β2.(lnp_bv)+β3. (lnvtrdus) +β4. (lnover)it+β5.(lnnush) +β6.(days)it (11)

Results

Table 5 presents the final results of each of the four models proposed, as two of the regressors (lnyield and days) did not show statistical significance (sig. > 0.05) in any of the models. Following Petersen [20] and Cameron and Trivedi [19], we present the results of all estimations.

Variable	Pooled Logit with Clustered Robust Standard Errors	PA Logit	Random Effects	Fixed Effects
lnp_bv	0.164**	0.179*	0.180**	0.146**
	(0.063)	(0.070)	(0.044)	(0.048)
lnvtrdus	-0.111**	-0.161**	-0.162**	-0.143**
	(0.039)	(0.049)	(0.035)	(0.043)
Lntover	0.164**	0.371**	0.400**	0.485**
	(0.058)	(0.089)	(0.051)	(0.051)
Lnnush	0.040*	0.032	0.030	0.017
	(0.018)	(0.018)	(0.019)	(0.024)
constant	0.583**	0.794**	0.813**	
	(0.144)	(0.193)	(0.135)	
N	6.747	6.747	6.747	6.732
Loglikelihod	-4,544.02		-4,503.61	-4,302.91
Wald χ^2	13.83	18.48	81.67	127.97
Sig. χ^2	0.001	0.001	0.000	0.000

Table 5: Logit Panel Data Models with Different Estimators

Notes: lnyield: natural logarithm of market dividends; lnp_bv: Natural logarithm of price/book value relation in the market; lnvtrdus: Natural logarithm of market negotiated value in million dollars; lntover: Natural logarithm of market turnover rate; lnnush: Natural logarithm of number of market negotiated stocks; days: Number of days with market operations. Standard errors between parentheses. *, ** is statically significant at 5% and 1%, respectively.

First, the statistical significance of the variable set is determined in all cases (sig. Wald χ^2). While the variable coefficient for the market capitalization is negative, the variable coefficients related to the price-to-book ratio and turnover rate are positive. The parameter of the variable related to the number of market negotiated stocks does not show statistical significance (sig. > 0.05) in three estimations.

Despite the fact that the variables dividend yield (lnyield) and days (days) are not significant, the evidence reinforces previous studies such as Bekaert and Harvey [13], which find a decrease in dividend yield and an improvement in growth opportunities. In our case, the price-to-book ratio is positive and statistically significant, showing a relationship with positive returns.

We find that size (lnvtrdus) is not related to positive returns, similar to the findings from the Harvey [13] study in which little relation existed between return and size. Another perspective, which Bekaert, Harvey and Lumsdaine [14] present, is that "if the price increase is permanent, it may reflect a long-lasting decrease in the cost of equity capital associated with the risk sharing benefits of capital market openings in emerging markets". However, since the coefficient of size is negative, even if reducing cost of capital, the 'return chasing' hypothesis it is a possibility in emerging markets.

Turnover rate (lntover) is related to liquidity, and it increases the probability of obtaining positive returns in emerging markets. However, we find weak evidence for trading volume because it is not conclusive due to most estimators not having significance.

Citation: Lopes Fávero LP, de Almeida JEF,Takamatsu RT (2014) Propensity for Growth of Stock Prices in Emerging Markets: A Logit Panel Approach. Bus Eco J 5: 88. doi:10.4172/2151-6219.100088

Additionally, according to Table 5, the estimated coefficients vary between the models. The fixed effect model provides considerably different parameter estimates from those obtained in the other models, and we present only the results of the regressors that vary over time (i.e., all regressor variables except for the constant). We do not consider 15 observations (related to 4 countries) with $\sum_{i=1}^{Ti} y_{it} = 0$ (dummy rental ways equal to 0) or $\sum_{i=1}^{Ti} y_{it} = T_i$ (dummyrent always equal to 1) in the modeling because no variations in yit occur over time.

With regard to the random effects model, lower standard errors exist than those obtained in the other models, with higher estimated coefficients, which demonstrates considerable variation in t-statistics.

After the modeling, we can detail predictions for each sample observation. Table 6 presents the success percentage for each of the proposed estimates, with an initial classification cutoff of 50%.

	Pooled Logit	**PA Logit**	**Random Effects**	**Fixed Effects**
Success Percentage	59.02	59.36	77.55	51.43

Table 6: Success Percentage for Each Estimate (Cutoff=50%)

Although the models with pooled logit and PA logit estimates present relatively similar parameters and demonstrate adequacy for predictive purposes, the estimation with random effects has a higher success percentage for the database used. Cameron and Trivedi [19] also present and discuss this procedure. So, for this estimation, the following classification was obtained (Table 7).

	Actual Events		**Total**
Model Classification	0	1	
0	2,125	334	2,459
1	1,857	5,443	7,300
Total	3,982	5,777	9,759
Correct Classification		77.55%	
Sensitivity		94.22%	
Specificity		53.36%	

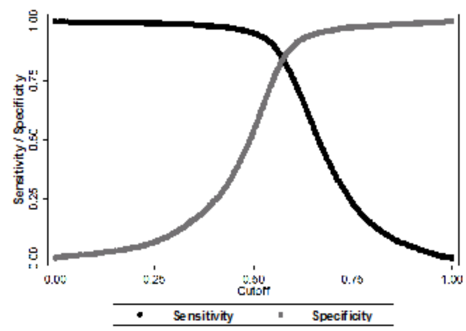
Table 7: Classification, Sensitivity and Specificity – Random Effect Model (Cutoff=50%)

In Table 7, the high predictive power of the random effects model is verified for those months when positive returns (sensitivity) occur, but this capacity is not found for months with negative returns (specificity), with cutoff set at 50%. When the cutoff is changed to 60%, however, specificity increases considerably to the detriment of sensitivity (Table 8). In general, the success percentage rises to 81.03% with the cutoff set at 60% (Table 8).

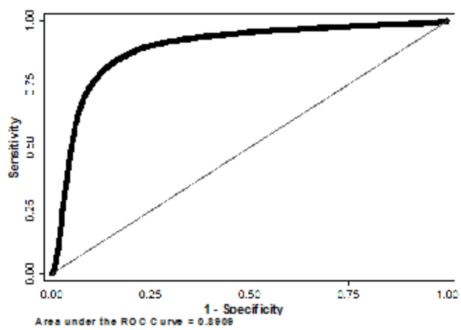
	Actual Events		**Total**
Model Classification	0	1	
0	3,544	1,413	4,957
1	438	4,364	4,802
Total	3,982	5,777	9,759
Correct Classification		81.03%	
Sensitivity		75.54%	
Specificity		89.00%	

Table 8: Classification, Sensitivity and Specificity – Random Effect Modeln (Cutoff 60%)

We present a broader analysis in Graph 5, which shows sensitivity and specificity performances when cutoff rates are changed. Thus, for the random effects model higher cutoff rates provide analysts with a higher success probability for months with negative returns. Similarly, lower cutoff rates lose this ability but permit defining months with positive returns with higher probability rates. The trade-off between sensitivity and specificity can be analyzed through the ROC curve, displayed in Graph 6.



Graph 5: Sensitivity and Specificity Analysis in Function of Cutoff



Graph 6: ROC Curve

Finally, according to Cameron and Trivedi [19], since the log odds interpretation for logit models applies to this case, as $\ln\left[p_i/(1-p_i)\right] = \alpha_i + X'_{it}\beta$ and, thus, $\partial \ln\left[p_i/(1-p_i)\right]/\partial X_{ji,t} = \beta_j$, the lnp_bv coefficient indicates, for example, that a unit increase in the natural logarithm of the market price-to-book value relation increases the log odds that the stock index will present a positive monthly return by 0.180 (i.e., 18.0%) ceteris paribus.

Final Considerations

In this study, the representativeness of capital market–related variables in developing countries prompts different questions about the relations among economic development, the representativeness of speculative capital, and the propensity towards the existence of positive returns in these markets.

The fact that the market-negotiated value negatively affects the stock indexes' propensity towards monthly growth may mean the presence of more short-term capital in these countries' markets; that is, the stronger presence of speculative capital determines the markets' movement, and this evidence is related to previous studies using returns.

This interpretation is also verified through the positive influence of the turnover rate on the growth probability of the stock indexes. Finally, we also identify the positive influence of the variable related to the price-to-book ratio on the probable existence of positive monthly returns, in line with Kennon [22].

This research contributes to the possibility of assessing different estimators through logit panel data modeling. According to Bartha et al. [23], many relevant studies use econometric techniques; without them, the validity of the studies' inferences maybe limited. Therefore, we decided to use various estimators to enhance the robustness of evidence and to permit comparisons. It is fundamental, however, that the choice of each statistical technique accords with what one wants to investigate.

We also highlight that governments and regulatory entities in emerging countries can adopt policies to stimulate their capital markets and monitor the factors, institutions, and rules that can affect the variables that we studying this paper.

According to Ramos-Rodriguez and Ruiz-Navarro [24], the origins of performance represent a central theme in research on understanding the variance components of specific behaviors over time. They also note that alternative approaches deserve further study with regard to the stock indexes. Researchers can include other regressors to create different models and to further the understanding of market-ruling mechanisms. Altering the analysis period can enhance a deeper understanding about how performance factors behave in emerging countries' stock markets.

Finally, this study fills an existing gap in literature on financial variables that affect the probable occurrence of positive returns in emerging countries' stock indexes. Thus, in view of the growth trend in capital market returns, which we measure here through the stock market indexes, this phenomenon needs further investigation, including macroeconomic variables that can affect the relations we analyze here.

References

1. Kwon CS, Shin TS, Bacon FW (1997) The effect of macroeconomic variables on stock market returns in developing markets. Multinational Bus Rev 5: 63-70.
2. King RG, Levine R (1993) Finance and growth: Schumpeter might be right. Quart J Econ 108: 717-737.
3. Levine R (1997) Financial development and economic growth: views and agenda. J Econ Lit 35: 688-726.
4. Rajan RG, Zingales L (1998) Financial dependence and growth. Am Econ Rev 88: 559-586.
5. Roe MJ, Siegel JI (2009) Political instability: its effects on financial development, its roots in the severity of economic inequality. J Comp Econ 39: 279-309.
6. Alexander D, Luigi Z (2004) Private benefits of control: an international comparison. J Financ 59: 537-600.
7. Steven TJ, Kevin B (2009) US elections and monthly stock market returns. J Econ Financ 33: 273-287.
8. Charles KD Adjasi, Nicholas Biekpe (2009) Do stock markets matter in investment growth in Africa? J Dev Areas 43: 109-120.
9. Tobin J (1969) A general equilibrium approach to monetary theory. J Money, Credit Bank 1: 15-29.
10. Von Furstenberg GM (1977) Corporate investment: does market valuation matter in the aggregate? Brookings Papers on Economic Activity 8: 347-408.
11. Claessens S, Dasgupta S, Glen J (1995) The cross-section of stock returns: evidence from emerging markets. Policy Research Working Paper Series.
12. Geert B, Campbell RH (1995) Time-varying world market integration. J Financ 50: 403–444.
13. Geert B, Campbell RH (2000) Foreign speculators and emerging equity markets. J Financ 55: 565–613.
14. Geert B, Campbell RH (2002) Research in emerging markets finance: looking to the future. Emerg Mark Rev 3: 429-448.
15. Geert Bekaert, Campbell R Harvey, Christian Lundblad (2003) Equity market liberalization in emerging markets. J Financ Res 26: 275-299.
16. Fávero LPL, Almeida JEF (2011) O comportamento dos índices de açõesempaísesemergentes: umaanálise com dados empainel e modeloshierárquicos. RevistaBrasileira de Estatística 72: 97-137.
17. Ian DG, Gaizka O, Daniel JT (2010) Correcting for cross-sectional and time-series dependence in accounting research. Account Rev 85: 483-512.
18. Greene WH (2008) Econometric analysis. (6th edn), Prentice Hall.
19. Cameron AC, Trivedi PK (2009) Microeconometrics using Stata. Stata Press, College Station, Texas.
20. Peteresen MA (2009) Estimating standard errors in finance panel data sets: comparing approaches. Rev Financ Stud 22: 435-480.
21. Wooldridge JM (2002) Econometric analysis of cross section and panel data. (2nd edn), MIT Press, Cambridge, Massachusetts.
22. Kennon J (2010) Price to cash flow ratio.
23. Mary E Bartha, William H Beavera, Wayne R Landsman Barth (2001) The relevance of the value-relevance literature for financial accounting standard setting: another view. J AccountEcon 31: 77-104.
24. Antonio-Rafael Ramos-Rodríguez, José Ruíz-Navarro (2004) Changes in the intellectual structure of strategic management research: a bibliometric study of the Strategic Management Journal, 1980-2000. Strat Manage J 25: 981-1004.