What do the cross-section of stock returns tell us about future economic conditions? *

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Abstract

This article develops leading indicators based on the cross-section of stock returns. The underlying assumption is that any information about future states of nature must be reflected in current stock prices. Three indicators are proposed: the approach employed by Allen et al. (2012), an approach based on Kelly e Jiang (2013) and an adaptation of the risk measure of Foster and Hart (2009) for cross-sectional data. We also analyze the first principal component of these indicators. The results show that the leading indicators proposed have high correlation with the economic activity and that they predict in general better than random walk and the average of previous observations.

Keywords: Tail risk, crisis.

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1 Introduction

Business cycles are part of economic dynamics. Nevertheless, the effects of its fluctuations could be damaging. Therefore, predicting the cycles is an important task for policy makers take actions to attenuate its effects. Though the term 'cycle' might suggest periodicity, economic contractions or expansions do not follow a clear pattern, which makes difficult its anticipation. Having this in mind, Leading Economic Indicators (LEA) turned out to be a relevant topic of investigation in economic literature. A LEA is simply an index or factor that changes before economic activity starts following a new trend or path. Most of the work about LEA is done using time series technics estimated from monetary aggregates and/or asset prices. In this paper we propose three LEAs based on stock returns in a point in time, i.e. based on a cross-section of stock market data.

Economic theory states that the price of an asset reflects its expected present value of future earnings adjusted by the risk. This result, jointly with the market efficiency hypothesis, tells us that any information about the future states of nature should be reflected in prices. Therefore, it is reasonable to imagine that current prices could provide relevant information for the construction of LEAs. In this context, a LEA is just a function of current asset returns.

Recently, cross-section data has been used in finance literature to infer future economic conditions. For instance, Allen et al. (2012) derive a catastrophic risk measure from an extreme inferior percentile of stock returns in a given point in time.[1] They show that this measure is capable of predicting downturns in economic activity six months ahead. Kelly and Jiang (2013) make use of cross-section of stock returns to estimate the tail-risk of the economy. They assume that the lower tail of the stock returns distribution follows the power law. This distribution depends on a time-variant parameter associated with the risk of disasters of the economy. They consider a pooling of stock return in a given month to estimate this parameter. The tail risk factor has significant explanatory power of future stock returns. This finding corroborates the hypothesis of Barro (2006), i.e. the expected return of assets is connected with disaster risk.

There is also the possibility of using cross-section data of options to extract information about future financial and economic conditions. For example, Siriwardane (2013) proposes a method to detect the aggregated risk of the economy based in the price of several portfolios of stock options. Bali et al. (2011) introduce a risk measure that generalizes the work of Aumann and Serrano (2007) and Foster and Hart (2009). They estimate this measure from a risk-neutral distribution extracted from the cross-section of options prices. The results reveal that the generalized risk measure foresees the 12-month ahead risk-adjusted stock return.

Following the approach based on the cross-section of asset returns, we propose three different LEAs and analyze its power for anticipating economic activity and financial conditions.[2] Additionally, we consider a fourth LEA, defined simply as a linear combination (the first prin-

[1]The catastrophic measure is the 1% percentile of stock returns of the financial sector in a given month.

[2]For convenience, we will use the term LEA to refer not only to economic activity indicators, but also to financial conditions, therefore acknowledging the misuse of the term.

cipal component) of the three primitive LEAs. The database used for estimation is always a pooling of monthly returns of stocks traded in the Brazilian Stock Exchange. The key point is to establish the definition of the LEA function. The first LEA is the 5% percentile of cross-section monthly stock returns. The second measure, proposed by Kelly and Jiang (2013), is the exponent of the power law. In their work, they test the explanatory power of this exponent in relation to stock returns. In fact, they aim to identify a factor connected with the disaster risk priced in the cross-section. In our paper, though using the same metric, we evaluate the relation of the exponent of the power law with economic activity. The third LEA is the risk measure of Foster and Hart (2009). They proposed an objective risk measure of gambles (risky assets), in the sense that it is independent of the decision-maker. This measure represents the critical value of wealth below which no risk would be taken, because to accept a game with a wealth smaller than this critic value can lead to bankruptcy. Thus, the lower this value, the lower is the risk.

It is worth noticing that all those measures were initially estimated using time-series data of asset returns instead of cross-section data. The first two measures were adapted, respectively, by Allen et al. (2012) and Kelly and Jiang (2013) for pooling data at a single point in time. Regarding to the third measure, we are not aware that our approach has ever been used before in the literature. Therefore, the application of Foster and Hart (2009) measure for cross-section data is a contribution of this paper. It is also worth mentioning that using data at a point in time, and not time-series data, means analyzing a wide aspect of recent financial informations instead of past ones to offer indicators of future economic and financial conditions. Finally, an additional contribution of this article is assessing the performance of LEAs for an emerging market economy - where business cycles are more volatile than in advanced economies.[3]

Our results show that the four measures have relation to economic activity until three months ahead. Monthly economic activity was measured by industrial production and by the economic activity index calculated by the Banco Central do Brasil. We also use a measure of financial conditions, the realized volatility of daily Ibovespa returns in a given month. The LEAs proposed also exhibit significant correlation to the future volatility of Ibovespa. Next, an out-of-sample exercise revealed that the four LEAs have a superior ability to predict economic activity than two classical benchmarks: the random walk and the historic average. For the future volatility of the Ibovespa, besides these two competitors, we also consider an autoregressive process of first order. In this case, the LEAs outperfom slightly the competitor.[4] Finally, although our focus is not the prediction of crisis indicators, our LEAs demonstrate having power of anticipation of some extreme events, such as the Asian and subprime crisis.

As Stock and Watson (2003) point out, asset prices are forward-looking and constitute a special and useful class of economic activity predictors. On the other hand, the same authors

[3]For a description of business cycles in emerging economies, we refer to Neumeyer and Perri (2005).

[4]The autoregressive property of volatility is a stylized fact well known in the finance literature. Therefore, to outperfom an autoregressive process of first order, even slightly, is impressive.

alert that empirical studies reveal a weak association between asset prices and activity indexes, especially in the case of stock returns.[5] This could be seen as a puzzle. Our findings contradict these works, since we show that stock returns have indeed the anticipation power for economic fluctuations. The key issue is to look at the tail of the distribution of a whole set of stock returns at a point in time. Possibly, the poor performance attributed to stocks as predictor of activity could have been in fact a modeling problem. Much of the literature consider time series models estimated using indexes of stock market, which disregard all information contained in extreme current prices.

The rest of the article is organized as follows. On Section 2, we describe the methodologies for constructing the LEAs. Section 3 presents the data base used in this study. Section 4 discusses the results. Section 5 contains the paper final remarks.

2 Methodology

The key feature of the methodologies for the construction of the LEAs proposed in this paper is that these indicators come from cross-section of stock returns. Let R_t^i be the return of asset $i = 1, \ldots, n$ at time t. A LEA at t is just a function of these n returns.

The first LEA we study is an inferior extreme percentile (or Value-at-Risk, VaR, in a financial language) of the set of monthly returns of cross section stock prices. This approach is used by Allen et al. (2012) which achieved good results in forecasting U.S. economic activity six months ahead. These authors estimate VaR by three different methods using stock returns of the financial system. Thus, they define a catastrophic indicator as the average of these three VaR. In this work, we estimate the VaR only through the percentile of returns. The reason is simple: The three series of VaR calculated by Allen et al. (2012) have strong correlation, indicating that one adds little information upon the other. Thus, the first LEA is:

$$LEA_{1,t} = \texttt{Percentile}\left(R_t^1, \ldots, R_t^n; \alpha_1\right), \tag{1}$$

where $\texttt{Percentile}\left(\cdot; \alpha\right)$ represents the α percentile of a dataset. Note that this metric depends on the choice of α_1. Allen et al. (2012) fix the percentile at 1%. In Brazil, there are fewer shares listed on the Stock Exchange than in the United States. In addition, several Brazilian stocks have very low liquidity. So, working with the level of 1% could generate estimation problems. Thus, we decided to choose the 5% percentile to evaluate our first LEA.

The second LEA is based on the work of Kelly and Jiang (2013). These authors employ the extreme value theory to model the behavior of asset prices. More specifically, they assume that the lower tail of the return distribution of an asset i follows the power law, i.e.:

[5]Stock and Watson (2003) argue that the most relevant relation between future economic activity and current financial assets prices occurs when the slope of the term structure of interest rates is used. However, as will be seen in the results section of this paper the slope of the yield curve is not related to economic activity in Brazil.

$$P_t\left(R_t^i < r \middle| R_t^i < u_t\right) = \left(\frac{r}{u_t}\right)^{a_i \zeta_t}, \quad (2)$$

where $P_t(\cdot)$ is the conditional probability on the information available up to t and u_t is a threshold which defines the lower tail of the returns distribution. The parameter ζ_t varies over time and represents the tail risk of the economy. On the other hand, a_i is a characteristic of each asset and represents the level of risk present in tail of asset i.

According to Kelly and Jiang (2013) a parsimonious procedure to obtain the tail risk of the economy is to use the estimator of Hill (1975). Applied to a set of monthly returns, this estimator takes the form:

$$\frac{1}{\zeta_t^{\text{Hill}}} = -\frac{1}{K_t}\sum_{k=1}^{K_t} \ln \frac{R_{k,t}}{u_t}, \quad (3)$$

where $R_{k,t}$ is the k-th monthly return smaller than the threshold u_t and K_T is the total number of returns in a month below u_t.[6] The second LEA is $IAA_{2,t} = \zeta_t^{\text{Hill}}$ with the lower tail threshold set as $u_t = \texttt{Percentile}\left(R_t^1, \ldots, R_t^n, \alpha_2\right)$. Again, we have to decide the value of α_2 to be used. Although Kelly and Jiang (2013) work with the 5% percentile, we set $\alpha_2 = 15\%$ because the small number of stock in our monthly sample does not allow us to work with a restrictive level as the 5% percentile.

Kelly and Jiang (2013) show that the exponent ζ_t has strong predictive power of the market portfolio return. This result is consistent with asset pricing theories that relate the stocks risk premium with disasters or other extreme risk events (see, eg, Barro, 2006 and Rietz, 1988). In this paper, we will apply the theory developed by Kelly and Jiang (2013) with another goal: To estimate economic fluctuations.[7]

The third LEA is an adaptation of the risk measure of Foster and Hart (2009) for cross-sectional data.[8] Foster and Hart propose an objective way to measure the risk of an asset, or, in the nomenclature of the authors, a game. It is objective in the sense that the measure does not depends on the decision maker. It depends only on the probability distribution of the game . The standard deviation is also an objective measure; however it is not monotonic (see Artzner et al., 1999). For each game, Foster and Hart (2009) show that there is a critical value of wealth, such that one should accept the game when wealth is above this value and rejects otherwise. Acceptting the game for wealth below the critical values leads to bad results in the

[6]Kelly and Jiang (2013) use daily stock returns within a month. In this article, we opted to work with monthly data for two reasons. First to maintain the same frequency (and therefore the same information content) used in the estimation of the other LEAs. Secondly, due to the difficulty of calculating daily returns precisely because of the low liquidity of some stocks in the Brazilian market.

[7]Although the main focus of the study of Kelly and Jiang (2013) is to explain the stock risk premium, they find that the exponent of the power law has a correlation of -11% with the economic activity index of the Chicago Fed (CFNAI).

[8]Closely linked with the risk measure of Foster and Hart (2009) is the risk index developed by Aumann and Serrano (2007). This index represents the inverse of the coefficient of absolute risk aversion of an investor who is indifferent between accepting or not risk. The measures of Aumann and Serrano (2007) and Foster and Hart (2009) share several of properties as demonstrated by Foster and Hart (2009).

long term, such as decrease in richness and even bankruptcy. On the other hand, acceptting the game for values above the critical wealth produces good results: solvency is guaranteed and the wealth grows in the long run. The risk of a game is defined as this critical value of wealth. Formally,

$$E\left[\ln\left(1+\frac{R}{FH(R)}\right)\right]=0, \tag{4}$$

where E is the expected value operator, R is the probability distribution of an asset return and $FH(R)$ is the Foster and Hart risk measure (the critical level of wealth that separates the situations to accept or reject the asset).

Foster and Hart (2009) also show that the FH measure enjoys a number of useful properties, such as subaditividade and monotonicity in relation to stochastic dominance. Besides these properties, another reason that motivated us to employ the FH measure is the results obtained by Bali et al. (2011). These researchers estimated a risk measure that generalizes the FH measure using the risk-neutral distribution extracted from options prices. In an application focusing in asset pricing, Bali et al. (2011) show that the generalized measure predicts well the risk-adjusted stock returns twelve months ahead. This indicates that the method of extracting information about risk proposed by Foster and Hart (2009) has explanatory power in relation to future uncertainty.

Theorem 1 of Foster and Hart (2009) requires two conditions on the distribution of R to the $FH(R)$ measure to be well defined (i.e., that there is a unique solution of Equation 4). These are: (i) game mean greater than zero , i.e. $E(R)$ >0; (ii) losses are possible, i.e. $P(R<0)>0$. If we assume homogeneous probabilities of the cross-section of stock returns, the first condition is not valid for several months of the sample. One solution to this problem is to add a constant to stock returns, simulating a risk free application. However, this would imply that in some months the second condition was not satisfied. Therefore, we abandon the hypothesis of equiprobable returns in the calculation of the third LEA. In fact, we propose a scheme of exponential weights with positive returns getting higher importance such that the two above conditions were met. That is, we define the third LEA as the positive solution of the following equation

$$\sum_{i=1}^{n}\lambda^{i-1}\ln\left(1+\frac{\bar{R}_t^i}{LEA_{3,t}}\right)=0, \tag{5}$$

where $\bar{R}$ is a descendant reordering of the original series of returns R and $\lambda\in[0,1]$ is the decay factor weight. In the empirical section we work with $\lambda=0.974$, since this is the maximum value of the decay factor that ensures that the positive average condition is satisfied in all months of the sample.

Finally, we study the predictive ability of a fourth LEA defined as the first principal component of the three previous LEAs. The motivation for using this linear combination of LEAs comes from a series of studies. For example, Rodriguez-Moreno and Peña (2013) show that the first principal component of portfolios of credit default swaps is the best measure of systemic risk among several factors tested by the authors. Futhermore, a successful finance literature considers a single source of uncertainty governing disaster risk (Gabaix, 2012), which leads us to suppose that the first principal component of the three primitive LEAs is connected with this risk factor.

3 Database

The sample for the LEAs construction is composed by monthly closing stock prices of Brazilian firms listed on the Brazilian stock exchange (BM&FBovespa) from August 1994 to March 2013. All prices are adjusted by dividends. There is only one share for each company, the one with most liquidity in the last month of the sample. 681 companies are in the database. Each company needs not to be present in all months of the sample period. For example, in March 2013 there are 311 stock prices. The smaller number of firms occurs in March 2003 (211) and the highest in 2008 (338).

The economic activity indexes on monthly basis used in this study are the Industrial Production (IP) and the Index of Economic Activity of the Banco Central do Brasil (IBC-Br). The IP series, collected in the IBGE website, has seasonal adjustment and comprises the same sample period of the stock prices. [9] The IBC-Br series, extracted from the Banco Central do Brasil website, also have seasonal adjustment and is only available since January 2003. Thus, this index includes data from January 2003 to February 2013. Both PI and IBC-Br are used in logarithmic changes. We also considered a measure of the economic condition constructed from the most relevant index of the Brazilian stock market (the BOVESPA Index - IBOVESPA): the IBOVESPA realized volatility (Vol-Ibov). This volatility, with monthly frequency, is the standard deviation of daily returns of the closing price of the Bovespa index within a given month.

4 Results

Following the recommendations of Stock and Watson (2003) the results will be presented in two subsections, one with the in-sample and another with the out-of-sample analysis. In Subsection 4.1 we discuss the fitting of the LEAs to changes in economic activity - measured by the industrial production index (IP) and economic activity index calculated by the Banco Central do Brasil (IBC-Br) - and to a measure of economic conditions drawn from financial data, the volatility of the Bovespa Index (Vol-Ibov); in Subsection 4.2 we compare the out of the sample forecast ability of the LEAs to the random walk and to the average of past data of these three activity indexes. For the Vol-Ibov we also parallel our predictions with

[9]Investors theoretically consider the seasonality of the economy in stock prices. Thus, when relating a risk measure extracted from stock prices to a metric of economic activity, it is recommended to adjust this last measure for seasonality.

the ones made by the autoregressive time series of order 1, which according to the Box-Jenkins methodology is the specification that best fits to this time series. [10] Before these two subsections, we present some descriptive statistics of our indicators and of the indexes.

The superior panel in Figure 1 shows the behavior of standardized indicators (mean zero and standard deviation one) during the sample period. The LEA_4, which is a linear combination of the other three LEAs, is not plotted in the panel to let the chart cleaner.[11] The three LEAs seem to vary jointly most of the time. In fact, the correlation between them is high but far from perfect: the correlation is 0.58 between LEA_1 and LEA_2, 0.44 between LEA_1 and LEA_3 and 0.32 between LEA_2 and LEA_3. One can also notice that these indicators have a strong negative skewness with extreme values occurring near the crises of Asia (October 1997), Russia (September 1998), and *subprimes* (September and October 2008). The LEA_1 and especially LEA_3 are also quite negative in the Brazilian crisis of Energy (second half of 2001). The indicators do not seem to react to the 1999 Brazilian crisis. In this crisis there was a sharp devaluation of the Brazilian real and the stock prices did not fall in the local currency. [12] As the LEAs use stock prices in the Brazilian currency, this may be the reason they do not capture this crisis. Among the indicators, LEA_3 is the one with more negative skewness and higher kurtosis. [13] At 5% level of significance the ADF test rejects the unit root hypothesis for all LEAs, for the variations of the economic activity indexes and for Vol-Ibov.

The inferior panel in Figure 1 shows the percentage changes of the economic activity indexes (IP and IBC-Br) and the negative of the volatility of the Bovespa index (Vol-Ibov). [14] The data for the IBC-Br are only released by the Banco Central do Brasil after January 2003. Notice that the two activity indexes have similar movements. Indeed, the correlation between IP and IBC-Br is 0.71 (both in percentage changes). However, the volatility of the changes in IP is greater than of the IBC-Br.[15] Similarly to LEAs, the skewness of these indexes are negative and it is greater again for IP.[16]

The Bovespa Index volatility (Vol-Ibov) presents a smoother behavior than the percentage variations of the activity indexes. This result is consistent with the fact that it has a first-order autocorrelation of 0.56, while the variations of the IP and the IBC-Br have first-order autocorrelations near zero (-0.05 and -0.03, respectively). Vol-Ibov seems to anticipate nega-

[10]We also use the Box-Jenkins methodology to detect the best specification for IBC-Br and IP, but for both time series the random walk itself is the process that best fits. The fact that changes in economic activity indexes follow a random walk is actually quite debated in the literature. For an interesting discussion of this point, see Cochrane (1988).

[11]The LEA_4, standardized to mean zero and standard deviation 1, is given by $LEA_4 = 0.454 \times LEA_1 + 0.424 \times LEA_2 + 0.375 \times LEA_3$. He explains 63.42% of the variation of the three primitive LEAs. The correlations of LEA_4 with the other LEAs are 0.86 with LEA_1, 0.81 with LEA_2 and 0.71 with LEA_3.

[12]In January 1999 the dollar/real quotation rose more than 64% and the Bovespa index appreciated about 18%.

[13]The skewness of LEA_1, LEA_2, LEA_3 and LEA_4 are respectively -1.59, - 0.78, -4.36 and -2.25. The kurtosis of LEA_1, LEA_2, LEA_3 and LEA_4 are respectively 4.34, 0.73, 25.96 and 9.75.

[14]The graphs show the negative values of the volatility of the Bovespa index just for better visualization of the relationship between the variables.

[15]The standard deviations for IP and IBC-Br are respectively 1.99% and 0.97 %, from 2003 onwards.

[16]the skewness for IP and IBC-Br are respectively -2.81 and -1.25 from 2003 onwards.

tive changes of the economic indexes in some moments as, for instance, the subprimes crisis . However, the correlation between the Vol-Ibov with the lag of one month and the indexes is not very high (0.10 and 0.14 for changes in IP and in IBC-Br, respectively). The contemporaneous correlations also are not as high as the correlation between the activity indexes (0.10 with IP and 0.23 with IBC-Br).

Figure 2 shows LEA_4, the percentage changes in IP and the negative of Ibovespa volatility. The other LEAs and the IBC-Br are not shown for a better visualization of the graph.[17] LEA_4 seems to present some lag correlation with IP and Vol-Ibov (with less visual evidence), which is an indication that this measure can be used to forecast these two variables. In the next section we will test whether these lagged correlations are statistically significant.

4.1 Fitting of the LEAs to the changes of the economic activity indexes

Tables 1, 2 and 3 show the results of the regression of the activity indexes (changes in IP, changes in the IBC-Br and Vol-Ibov) against each LEA with lags of one, two and three months. Since we are working with monthly data, the observations are overlapped when the LEAs are lagged for more than one month in relation to the dependent variables. In this case, OLS based tests and even the estimator based on Newey-West (1987) standard errors are distorted. Thus, all statistics are calculated using the procedure of Hodrick (1992) that, according to Ang and Bekaert (2007), provides the more conservative standard error correction among the methods used to circumvent the overlap problem. All the three tables show that, in general, the lagged LEAs have a significant correlation with the activity indexes.

Table 1 shows the eight regressions for the IP: a regression for each LEA and a regression for each LEA with the lagged IP as control. Panels A, B and C refer to the LEAs with lags of one, two and three months, respectively. For the LEAs with lag of one month, all coefficients are statistically significant meaning that the lagged LEAs have significant correlation with IP. By adding the lagged IP as control, the lagged LEAs are still statistically significant. With two lags, the LEA_2 loses significance, but the adjusted R^2 of the regressions of the other three LEAs increases. With three lags, LEA_2 and LEA_4 are significant. Therefore, LEA_4 (the first principal component) is significant for all three lags in explaining changes in IP.

Table 2 is similar to Table 1, except that the dependent variable in the regressions is IBC-Br. As for IP, all coefficients are statistically significant for LEAs with lag of one month and only LEA_2 is not significant when the lag is two months. Note that for all regressions the adjusted R^2 is greater than for the regressions when the IP is the dependent variable, which is a satisfactory result since the IBC-Br is a broader activity index. However, when the lag is three periods, no LEA is significant.

In Table 3, the dependent variable is a measure of economic conditions extracted from

[17]There is almost no loss of information because LEA_4 has strong correlation with the other LEAs, with the same occurring for the correlation between the changes in IBC-Br and IP.

financial data, the volatility of the Bovespa Index (Vol-Ibov). This is the only activity index for which the lag of the dependent variable is significant.[18] In some cases the LEAs lose significance with the presence of this control. LEA_4 (principal component) is the only LEA significant for all lags, even with the presence of the autoregression control.

As we can see in the tables, the LEA_4 has the best fitting to the changes in economic activity indexes, since it has a greater number of significant coefficients in the regressions. Moreover, it outperforms the LEA_2 and LEA_3 if we compare the models by the adjusted R^2. Thus, it seems that the combination of LEAs in a single source of uncertainty can be a good predictor for economic activity. The second best LEA is undoubtedly LEA_1.

The results in this section provide insights about the ability of current stock returns to work as indicators of future activity. Although asset prices are commonly thought as important sources of anticipation of economic conditions, empirical studies show that the predictive power of stock prices is not satisfactory (see, for instance, Stock and Watson, 2003). One possible reason for this flaw could be the fact that fluctuations in asset prices may be due more to changes in risk premium than in fundamentals (see Campbell, 2003). Another explanation would be linked to the way of future expectations are extracted from stock returns. In this article, we focus on this second point. Our findings reveal that the tail of the cross-section of stock returns has explanatory power up to three months ahead. Possibly, previous works have not been successful on this issue by considering the return of a stock index as leading indicator, thereby neglecting information on the variability and on the tail of current cross-section returns.

Another important observation concerns the superiority of the tail of stock returns in relation to the slope of the yield curve as a predictor of economic conditions. Several studies (see, for instance, Estrella and Hardouvelis, 1991) show that the slope of the yield curve is the main leading indicator of economic activity extracted from asset prices. The slope of the yield curve is the difference between the long and short interest rate. A positive slope may be related to growth, while an inverted yield curve would mean recession. Following Estrella and Hardouvelis (1991), we test the slope of the yield curve as a predictor of economic conditions for the Brazilian market. Specifically, we run regressions of the activity indexes (changes in PI, changes in IBC-Br and Vol-Ibov) against the slope of the yield curve with lags ranging from one to twelve months. The slope was defined as the difference between the interest rates of five years and one month. The data cover the period from September 2004 until March 2013.[19] Contrary to expectations, the coefficients of the slope in all regressions are not statistically significants and the R^2s are extremely low (less than 1%). The weak predictive ability of the slope can be related to the fact that business cycles of emerging markets have different characteristics from developed economies (Neumeyer and Perri, 2005). Therefore, the methodology proposed in this article provides a predictor of economic activity for an emerging

[18] Bollerslev (1986), in the article in which the GARCH models are developed, shows that the volatility has significant autocorrelation.

[19] Before September 2004 there are no data on Brazilian long-term interest rate.

market in which the most common activity indicator extracted from asset prices does not fit well.

4.2 Out of the sample comparison of LEAs with *benchmarks*

Besides checking the in-sample fitting of LEAs to the activity indexes in the previous section, we parallel the LEAs forecasts with the prediction based on the random walk (RW) and the average of past data (Average). For the Vol-Ibov we also compare our forecasts with the autoregressive time series of order 1, which is the model that best fits to this time series by the Box-Jenkins methodology.

The first 60 months were used as "critical mass" for the first prediction. Accordingly, as the first observation of Vol-Ibov in our sample is from August 1994, the first forecast is for August 1999. As IP is a variable in difference, the first prediction is performed for one month later. Since the IBC-Br is only available from January 2003, the first forecast for this index is for February 2008. All prior information is considered for the forecast of the activity indexes. The estimation of the coefficients is performed by the regression:

$$Y_{t+lag} = \hat{\alpha} + \hat{\beta} LEA_t + error_{t+lag}, \tag{6}$$

where Y is the activity index. Let τ be the last month used to estimate the coefficients. Therefore, the forecast of the activity index for $\tau + lag$ is given by:

$$E(Y_{\tau+lag}) = \hat{\alpha} + \hat{\beta} LEA_\tau. \tag{7}$$

In this work, we use $lag = 1, 2, 3$.

We compare the forecasts of each LEA with those performed by the random walk (RW) and the average of the activity index (Average). The forecast by the RW is given by $E(Y_{\tau+lag}) = Y_\tau$, while the forecast by the Average is given by

$$E(Y_{\tau+lag}) = \frac{\sum_{t=1}^{\tau} Y_t}{n},$$

where n is the number of observations in the sample until τ. Table 4 shows the sum of squared errors (SSE) of the forecasts of the activity variables (IP, IBC-Br and Vol-Ibov). The forecasts are made by LEAs, the RW and the Average with lags of 1, 2 and 3 months. At the bottom of the table is the t statistic of the Diebold and Mariano (1995) test in which the alternative hypothesis is that the errors of two predictions are different.

When forecasting one month ahead, the LEAs outperform the other methods for the two activity indexes, IP and IBC-Br, in all 16 comparisons. By the Diebold-Mariano test (D-M test, 1995), when forecasting IP, LEA_2 and LEA_4 are significantly better than the average and all the four LEAs are significantly better than RW. For the IBC-Br, only the LEA_3 does not predicted significantly better than the average. When forecasting Vol-Ibov, LEA_1 is the predictor that have fewer errors. The only case when LEAs predict significantly worse occurs for this variable (LEA_2 and LEA_3 when faced with RW and Vol-Ibov (-1)). However, when comparing to the Average, LEAs forecast significantly better Vol-Ibov, except for LEA_3.

When forecasting two months ahead, the LEAs once again surpass the other methods for the two activity indexes in all 16 comparisons. By the D-M test, the LEAs statistically outperform RW when forecasting IP, but, for IBC-Br, the superiority of LEAs is not statistically significant. When predicting Vol-Ibov the best indicators are LEA_1 and LEA_4 and all four LEAs outperform significantly better the Average.

Finally, for the forecast time of three months, the LEAs are always superior to the RW when forecasting both activity indexes (always statistically significant when the activity index is the IP). The Average has almost always fewer errors when predicting these two indexes (however, the Average is not significantly superior). For Vol-Ibov, once again LEA_1 and LEA_4 surpass the other predictors (including here Vol-Ibov(-1)) . All LEAs statistically outperform the Average and LEA_1 is the only one LEA that statistically surpass the RW. The results of this section show that in general the proposed LEAs outperform their classic competitors (RW and Average), with better performance for LEA_1 and LEA_4. When forecasting Vol-Ibov, LEA_1 and almost always LEA_4 outperform Vol-Ibov(-1) which is an important result, since the autoregressive property is a stylized fact for volatility.

5 Final Remarks

This article develops leading economic activity indicators based on the cross section returns of stocks. The underlying assumption is that any information about future states of nature must be reflected in stock prices.

Four indicators are proposed: the approach used by Allen et al. (2012), which is simply a tail percentile of stock returns at a given point in time; an indicator based on Kelly and Jiang (2013) approach that uses the extreme value theory to model the behavior of asset prices; an adaptation of the Foster and Hart (2009) risk measure for cross-sectional data; and the first principal component of these three indicators.

The leading indicators proposed are tested for forecasting of two monthly indexes of economic activity: the Industrial Production and the Index of Economic Activity of the Banco Central do Brasil (IBC-Br). We also use the leading indicators to forecast the realized volatility of the Bovespa Index, which would be a proxy of the economic condition estimated from financial data.

The results show that the leading economic activity indicators extracted from cross-sectional data of stocks are highly correlated with changes in the economic indexes. Moreover, the indicators in general predict better these economic indexes than the random walk and the average of previous observations. In addition, the indicators have slightly better performance for forecasting the realized volatility than the lagged realized volatility, which is also an important result, since the autoregressive property is a stylized fact well known in the financial literature.

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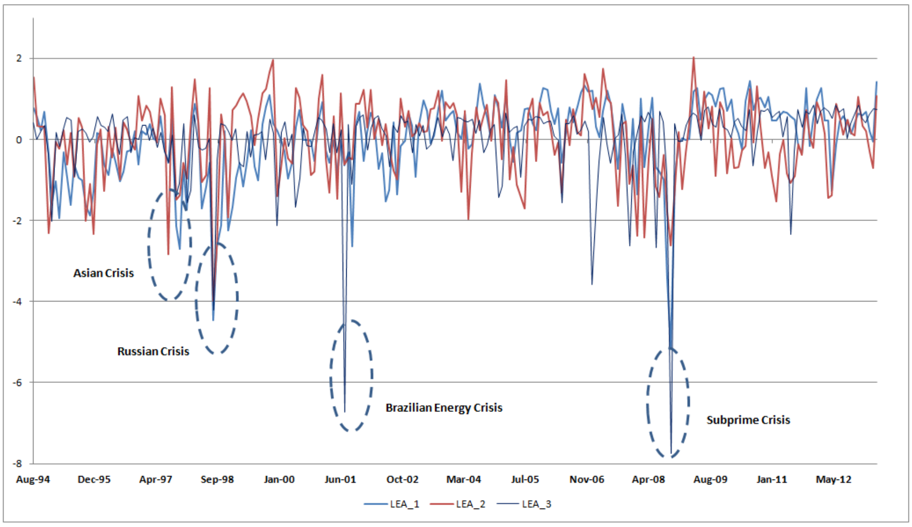
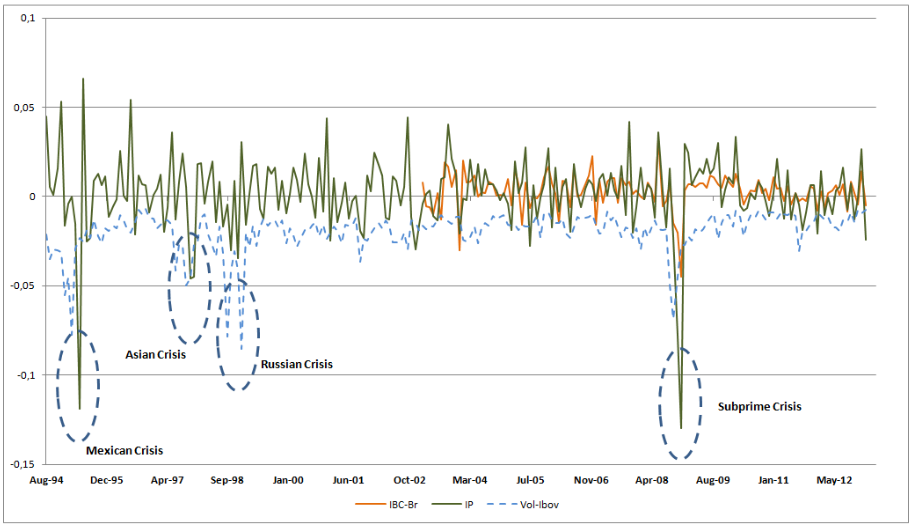
(a) LEA

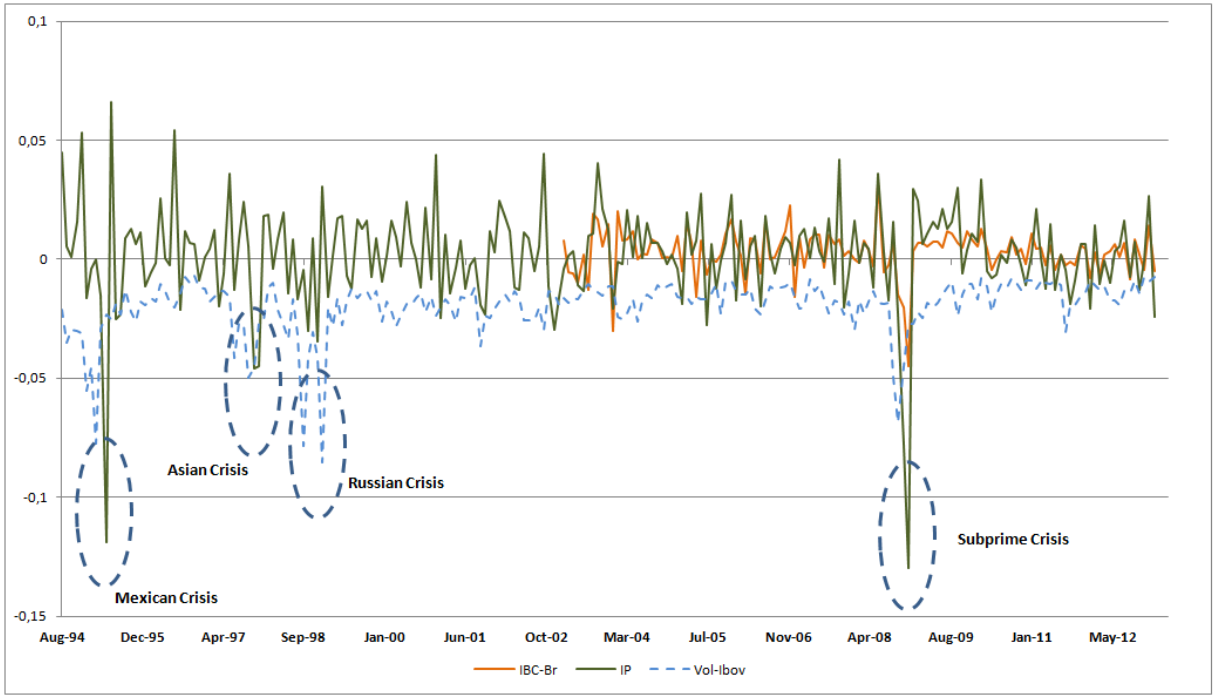


(b) Activity



Notes: The figure shows: in panel (a) the behavior of three leading activity economic indicators (LEAs) and; in panel (b) the changes in economic activity indexes on a monthly basis - Industrial Production (IP) and the Economic Activity Index Banco Central do Brasil (IBC-Br) - and the negative of the realized volatility of the Bovespa Index (Vol-Ibov). All three LEAs are constructed from the cross-section of stock returns. The LEA_1 is the approach used by Allen et al. (2012), the 5% percentile. The LEA_2 is based on Kelly and Jiang (2013) approach that uses the extreme value theory to model the behavior of asset prices. The LEA_3 is an adaptation of the Foster and Hart (2009) risk measure for cross-sectional data. The IP and the IBC-Br are seasonally adjusted. Vol-Ibov is the population standard deviation of daily returns of the closing values of the Bovespa index within a given month. The observations of the LEAs, the IP and the Vol-Ibov comprise the period from August 1994 to February 2013 while the observations of the IBC-Br comprise the period from February 2003 to February 2013.

Figura 1: Leading Indicators and Economic Activity Indexes



Notes: The figure shows the behavior of LEA_4, changes in Industrial Production (IP) and the negative of the realized volatility of the Bovespa Index (Vol-Ibov) from August 1994 to May 2013. LEA_4 is the first principal component of the other three LEAs. The IP is seasonally adjusted. Vol-Ibov is the population standard deviation of daily returns of the closing values of the Bovespa index within a given month.

Figura 2: LEA_4 and Economic Activity Indexes

Tabela 1: Regression Results- Industrial Production

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: Lag of 1 month								
LEA_1	0.0053***	0.0055***						
	(0.0019)	(0.0018)						
LEA_2			0.0039**	0.004**				
			(0.0018)	(0.0017)				
LEA_3					0.0043**	0.0044**		
					(0.0019)	(0.0019)		
LEA_4							0.0057***	0.0059***
							(0.0019)	(0.0018)
IP		-0.0892		-0.0643		-0.0615		-0.0823
		(0.1253)		(0.1313)		(0.1312)		(0.126)
Ajusted R^2	0.062	0.070	0.034	0.038	0.042	0.046	0.072	0.079
Panel B: Lag of 2 months								
LEA_1	0.0068**	0.007**						
	(0.0033)	(0.0034)						
LEA_2			0.0025	0.0026				
			(0.0021)	(0.0022)				
LEA_3					0.0066**	0.0067**		
					(0.0033)	(0.0033)		
LEA_4							0.0067**	0.0068*
							(0.0034)	(0.0035)
IP		-0.0636		-0.0233		-0.0304		-0.0514
		(0.0599)		(0.0501)		(0.0575)		(0.0594)
Adjusted R^2	0.103	0.107	0.015	0.015	0.099	0.100	0.099	0.102
Panel C: Lag of 3 months								
LEA_1	0.0018	0.0017						
	(0.0016)	(0.0017)						
LEA_2			0.0027**	0.0026**				
			(0.0011)	(0.0012)				
LEA_3					-0.0003	-0.0003		
					(0.0011)	(0.0011)		
LEA_4							0.0019***	0.0018**
							(0.0007)	(0.0008)
IP		-0.0138		-0.0101		-0.0014		-0.0114
		(0.0747)		(0.0702)		(0.067)		(0.0713)
Ajusted R^2	0.008	0.007	0.017	0.016	0.000	0.000	0.008	0.007

Notes: The table presents regressions of the change in Industrial Production (IP) against the leading activity economic indicators (LEAs). There is a regression for each LEA and a regression for each LEA with the lagged IP as control. The IP is seasonally adjusted. The LEAs are constructed from the cross-section of stock returns. LEA_1 is the approach used by Allen et al. (2012), the 5% percentile. LEA_2 is based on Kelly and Jiang (2013) approach that uses the extreme value theory to model the behavior of asset prices. LEA_3 is an adaptation of the Foster and Hart (2009) risk measure for cross-sectional data. LEA_4 is the first principal component of the other three LEAs. The data on a monthly basis comprise the period from September 1994 to March 2013. *, ** and *** denote significance at 10%, 5% e 1%, respectively. Numbers in brackets represent the standard error of the estimators. The standard errors were calculated by Hodrick (1992).

Tabela 2: Regression Results- IBC-Br

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: Lag of 1 month								
LEA_1	0.0045***	0.0046***						
	(0.0007)	(0.0007)						
LEA_2			0.0032***	0.0032***				
			(0.001)	(0.001)				
LEA_3					0.0019***	0.002***		
					(0.0007)	(0.0007)		
LEA_4							0.0039***	0.004***
							(0.0006)	(0.0005)
IBC-Br		-0.0927		-0.0421		-0.0574		-0.083
		(0.1209)		(0.1384)		(0.1465)		(0.1297)
Adjusted R^2	0.160	0.170	0.097	0.100	0.043	0.047	0.145	0.154
Panel B: Lag of 2 months								
LEA_1	0.0042**	0.0041**						
	(0.002)	(0.002)						
LEA_2			0.0017	0.0016				
			(0.0016)	(0.0015)				
LEA_3					0.0036**	0.0034**		
					(0.0014)	(0.0014)		
LEA_4							0.0039**	0.0068**
							(0.0018)	(0.0018)
IBC-Br		0.059		0.1095***		0.0667		0.0654
		(0.0441)		(0.0296)		(0.0416)		(0.0405)
Adjusted R^2	0.142	0.146	0.027	0.039	0.143	0.147	0.143	0.148
Panel C: Lag of 3 months								
LEA_1	0.0019	0.002						
	(0.0016)	(0.0016)						
LEA_2			0.0012	0.0013				
			(0.0014)	(0.0015)				
LEA_3					-0.0002	-0.0002		
					(0.0005)	(0.0006)		
LEA_4							0.0011	0.0012
							(0.0011)	(0.0011)
IBC-Br		-0.0434		-0.0211		-0.0116		-0.032
		(0.0898)		(0.0829)		(0.0776)		(0.0888)
Adjusted R^2	0.028	0.032	0.014	0.016	0.000	0.001	0.012	0.014

Notes: The table presents regressions of the change in the Economic Activity Index Banco Central do Brasil (IBC-Br) against the leading activity economic indicators (LEAs). There is a regression for each LEA and a regression for each LEA with the lagged IBC-Br as control. The IBC-Br is seasonally adjusted. The LEAs are constructed from the cross-section of stock returns. LEA_1 is the approach used by Allen et al. (2012), the 5% percentile. LEA_2 is based on Kelly and Jiang (2013) approach that uses the extreme value theory to model the behavior of asset prices. LEA_3 is an adaptation of the Foster and Hart (2009) risk measure for cross-sectional data. LEA_4 is the first principal component of the other three LEAs. The data on a monthly basis comprise the period from September 1994 to March 2013. *, ** and *** denote significance at 10%, 5% e 1%, respectively. Numbers in brackets represent the standard error of the estimators. The standard errors were calculated by Hodrick (1992).

Tabela 3: Regression Results- Volatility of the Bovespa Index

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: Lag of 1 month								
LEA_1	-0.0063***	-0.0038**						
	(0.0011)	(0.0016)						
LEA_2			-0.0039***	-0.0021*				
			(0.0012)	(0.0011)				
LEA_3					-0.003**	-0.0012		
					(0.0013)	(0.0012)		
LEA_4							-0.0057***	-0.0032**
							(0.0011)	(0.0015)
Vol-Ibov		0.3433***		0.4969***		0.528***		0.4055***
		(0.131)		(0.0985)		(0.1026)		(0.1165)
Adjusted R^2	0.304	0.382	0.119	0.349	0.070	0.328	0.245	0.372
Panel B: Lag of 2 months								
LEA_1	-0.0037***	-0.0013						
	(0.0007)	(0.0013)						
LEA_2			-0.002**	-0.0006				
			(0.0008)	(0.0006)				
LEA_3					-0.0026***	-0.0014		
					(0.0008)	(0.001)		
LEA_4							-0.0035***	0.0068**
							(0.0007)	(0.0007)
Vol-Ibov		0.3304***		0.3873***		0.368***		0.3325***
		(0.1156)		(0.0502)		(0.0589)		(0.0662)
Adjusted R^2	0.105	0.173	0.031	0.168	0.053	0.179	0.094	0.177
Panel C: Lag of 3 months								
LEA_1	-0.0035***	-0.002*						
	(0.0009)	(0.0012)						
LEA_2			-0.0022**	-0.0011				
			(0.0009)	(0.0009)				
LEA_3					-0.0016***	-0.0006		
					(0.0006)	(0.0006)		
LEA_4							-0.0031***	-0.0017**
							(0.0007)	(0.0007)
Vol-Ibov		0.2179**		0.2996***		0.3191***		0.2526***
		(0.0941)		(0.0718)		(0.0595)		(0.0762)
Adjusted R^2	0.096	0.137	0.036	0.128	0.020	0.121	0.076	0.134

Notes: The table presents regressions of the volatility of the Bovespa Index (Vol-Ibov) against the leading activity economic indicators (LEAs). There is a regression for each LEA and a regression for each LEA with the lagged Vol-Ibov as control. Vol-Ibov is the population standard deviation of daily returns of the closing values of the Bovespa index within a given month. The LEAs are constructed from the cross-section of stock returns. LEA_1 is the approach used by Allen et al. (2012), the 5% percentile. LEA_2 is based on Kelly and Jiang (2013) approach that uses the extreme value theory to model the behavior of asset prices. LEA_3 is an adaptation of the Foster and Hart (2009) risk measure for cross-sectional data. LEA_4 is the first principal component of the other three LEAs. The data on a monthly basis comprise the period from September 1994 to March 2013. *, ** and *** denote significance at 10%, 5% e 1%, respectively. Numbers in brackets represent the standard error of the estimators. The standard errors were calculated by Hodrick (1992).

Tabela 4: Out-of-the-sample Forecasts

	1 month			2 months			3 months		
	IP	IBC-Br	Vol-Ibov	IP	IBC-Br	Vol-Ibov	IP	IBC-Br	Vol-Ibov
	Sum of squared forecast errors								
LEA1	0.0547	**0.0042**	**0.0067**	0.0554	**0.0049**	**0.0100**	0.0597	0.0066	**0.0100**
LEA2	0.0566	0.0049	0.0123	0.0590	0.0057	0.0123	**0.0585**	0.0059	0.0120
LEA3	0.0574	0.0054	0.0146	0.0547	0.0050	0.0123	0.0603	**0.0058**	0.0123
LEA4	**0.0537**	0.0044	0.0094	**0.0544**	**0.0049**	0.0105	0.0594	0.0062	0.0107
RW	0.1080	0.0092	0.0078	0.1160	0.0092	0.0119	0.1233	0.0102	0.0140
Average	0.0592	0.0058	0.0143	0.0591	0.0058	0.0143	0.0589	**0.0058**	0.0141
Vol-Ibov(-1)			0.0076			0.0112			0.0112
	Diebold-Mariano Test								
LEA1 x RW	-1.82*	-1.65*	-1.00	-2.28*	-1.42	-0.96	-2.81*	-1.25	-2.01*
LEA1 x Average	-1.61	-1.86*	-4.64*	-0.57	-0.83	-7.99*	0.52	1.40	-9.17*
LEA1 x Vol-Ibov(-1)			-0.90			-1.16			-1.35
LEA2 x RW	-1.75*	-1.40	2.42**	-2.11*	-1.08	0.15	-2.86*	-1.45	-0.89
LEA2 x Average	-2.00*	-1.72*	-1.96*	-0.07	-0.33	-5.91*	-0.20	0.57	-4.83*
LEA2 x Vol-Ibov(-1)			4.57**			1.14			0.91
LEA3 x RW	-1.68*	-1.16	2.01**	-2.30*	-1.37	0.22	-2.79*	-1.51	-0.79
LEA3 x Average	-0.52	-0.73	0.14	-0.84	-0.95	-3.92*	1.44	0.59	-5.46*
LEA3 x Vol-Ibov(-1)			2.55**			1.61			1.57
LEA4 x RW	-1.85*	-1.54	0.93	-2.32*	-1.44	-0.77	-2.82*	-1.38	-1.62
LEA4 x Average	-1.65*	-1.91*	-3.24*	-0.78	-0.92	-7.49*	0.26	1.38	-7.48*
LEA4 x Vol-Ibov(-1)			1.39			-0.78			-0.40

Notes: The table presents the results of the out-of-the-sample forecasting of the IP, IBC-Br and Vol-Ibov for one, two and three months ahead. The predictions are made by the leading activity economic indicators (LEAs), the Random Walk (RW) and the average of past observations (Average). For the Vol-Ibov we also parallel our predictions with the ones made by the autoregressive time series of order 1 (Vol-Ibov(-1)). The first 60 months were used as "critical mass´´ for the first prediction. As the first observation of Vol-Ibov in our sample is from August 1994, the first forecast is for August 1999. As IP is a variable in difference, the first prediction is performed for a month later. Since the IBC-Br is only available from January 2003, the first forecast for this index is for February 2008. All previous information is considered for predicting the index of activity in any month. The upper part of the table contains the sum of squares of the forecasts errors. Values in bold indicate the best prediction for each pair (time forecast and activity indicator). The bottom of the table shows the t statistic of the Diebold-Mariano Test (1995). The alternative hypothesis is that the errors of two predictions are different: if $t < -1.645$, errors of prediction through the first variable are smaller than through the second variable; if $t > 1.645$, errors of prediction through the second variable are smaller than through the first variable. * indicates that the LEA outperformed the benchmarks. ** Indicates that the benchmark has outperformed the LEA.