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USE MACROECONOMICS OR MARKET INDICATORS TO UNDERSTAND RETURNS ON BRAZILIAN REAL ESTATE FUNDS?

USAR MACROECONOMIA OU INDICADORES DE MERCADO PARA ENTENDER OS RETORNOS DOS FUNDOS IMOBILIÁRIOS BRASILEIROS?

¿UTILIZAR MACROECONOMÍA O INDICADORES DE MERCADO PARA ENTENDER LOS RENDIMIENTOS DE LOS FONDOS INMOBILIARIOS BRASILEÑOS?

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ABSTRACT
The present work aims to apply the Dynamic Factor Model to extract common factors from real estate investment funds (FIIs) from 2013 to 2019. The values used were monthly closings of the funds' shares and a subset divided between brick-and-paper funds. For the analysis, dynamic factor models were created using economic and market indicators as explanatory variables, the dependent variables were the main factors extracted from the main components analysis for 78 selected funds, and the models were estimated by OLS (Ordinary Least Squares). This work's main findings were that most returns are given by idiosyncratic components, that the dynamic factors model is a method that can be applied as a form of forecasting, and that market indicators are more important for predicting FIIs than economic indices.

Keywords: Forecast; Modeling; Real Estate Funds; Dynamic Factors.

RESUMO
O presente trabalho objetiva aplicar o Modelo de Fatores Dinâmicos para extrair fatores comuns de fundos de investimentos imobiliários (FIIs) no período de 2013 a 2019. Os valores utilizados foram de fechamentos mensais das quotas dos fundos e

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também subconjunto divididos entre fundos de tijolo e de papel. Para a análise, foram elaborados modelos de fatores dinâmicos utilizando como variáveis explicativas indicadores econômicos e de mercado, as variáveis dependentes foram os principais fatores extraídos a partir da análise de componentes principais para 78 fundos selecionados, os modelos foram estimados por OLS (Ordinary Least Squares). O estudo trouxe como principal achado que a maior parte dos retornos é dado por componentes idiossincráticos, que o modelo de fatores dinâmicos é um método que pode ser aplicado como forma de previsão, e, indicadores de mercado são mais importantes para prever FIIs que índices econômicos.

Palavras-chaves: Previsão; Modelagem; Fundos Imobiliários; Fatores Dinâmicos.

RESUMEN

El presente trabajo tiene como objetivo aplicar el Modelo de Factores Dinámicos para extraer factores comunes de los fondos de inversión inmobiliarios (FII) en el período de 2013 a 2019. Los valores utilizados fueron los cierres mensuales de las acciones de los fondos y también un subconjunto dividido entre ladrillo y fondos de mortero. Para el análisis se crearon modelos factoriales dinámicos utilizando indicadores económicos y de mercado como variables explicativas, las variables dependientes fueron los principales factores extraídos del análisis de componentes principales para 78 fondos seleccionados, los modelos fueron estimados mediante MCO (Mínimos Cuadrados Ordinarios). El principal hallazgo del estudio fue que la mayoría de los rendimientos están dados por componentes idiosincrásicos, que el modelo de factores dinámicos es un método que puede aplicarse como forma de pronóstico y que los indicadores de mercado son más importantes para predecir los FII que los índices económicos.

Palabras clave: Pronóstico; Modelado; Fondos Inmobiliarios; Factores dinámicos.

1 INTRODUCTION

The real estate fund market has been studied from different perspectives. Evidence suggests that shocks in the prices of real estate assets, which are the assets that underlie real estate funds, influence the stability of the banking system (Deng and Zeng, 2019) and also changes in the degree of substitution between residential and commercial properties affect the transmission of shocks sectors in macroeconomics (David, Huang and Sapci, 2022). On the other hand, technological shocks and changes in monetary policy are correlated with real estate asset prices (Plakandaras et al., 2020; Tse and Rodgers, 2014; Nneji, Brooks, and Ward, 2013; Bouchouicha and Ftiti, 2012). Therefore, real estate fund prices are relevant for understanding several aspects related to the economy in general and the sector itself.

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In addition to the relationship between the macroeconomy and property prices, evidence suggests that the price of real estate funds also correlates with the economy as a whole. Wu and Wang (2024) found a positive relationship between GDP and returns on real estate funds in different income quantiles, in addition to showing that unemployment rates and effective interest rates also have a positive relationship with returns. Another important factor for understanding the returns on real estate funds is the uncertainty in the economic policy practiced by a government (Sadhwani et al., 2019). It can therefore be seen that expanding the understanding of the influence of macroeconomic and market variables through methods other than those used constitutes a contribution to the literature.

In this context, this article aims to evaluate the predictive performance of macroeconomic variables and real estate market indices about common dynamic factors of FIIs. To this end, subsamples of FIIs that are characterized as Brick and Paper were created. These brick funds are represented by physical properties: stores and supermarkets; Bank agencies; shopping malls; warehouses and others. On the other hand, receivables or paper funds are made up of bonds or securities linked to the real estate sector. The method chosen for data analysis was the dynamic factors model, which allows capturing the dynamics of the series of interest based on the common source of variation in the series itself or variables of interest, and the idea is to use a set of related variables to this source and, by extracting the common variation component between them, obtain an approximation of this unobservable source.

The empirical field of study consists of a set of 99 Real Estate Funds belonging to B3. In December 2020, the class of FIIs on B3 had 537 Funds registered by the CVM, of which 301 were listed and available for sale on the stock exchange, totaling R$124 billion in Net Equity. The analysis period was from 2013 to 2019, using the monthly closing values of the fund's shares. For the analysis, the challenge was to obtain the main dynamic factors of FIIs and estimate models based on macroeconomic variables and market indices.

This work was prepared following the steps developed by Valk, Mattos, and Ferreira (2019), who are the authors of the Nowcasting package and developed algorithms in the R programming language to estimate and predict economic variables using Dynamic Factor Models. The researchers used as a basis the study by Giannone, Reichlin, and Small (2008a) and Stock and Watson (2016).

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To develop the analysis, factors were estimated based on Principal Components Analysis (PCA) and the IC-Factor Indicator from the Nowcasting package. Then, multiple linear regression models were adjusted with the two main factors of the real estate fund return series as the dependent variable and economic variables such as IBOV, IPCA, IGPM, Exchange, IFIX, NTN-B, IMA-B, IVG -R, MVG-R, and Fipe as explanatory variables. The main finding was that most returns are given by idiosyncratic components and that the estimated factors of FIIs are complex and there are a variety of indicators that reflect this market.

To complement the analysis, the data set of FII returns was separated into Brick FIIs and Paper FIIs, and estimated using real estate market indicators. To achieve the objective, this research is divided into this introduction, the literature review, the methodology section, and the analysis of the results.

2 LITERATURE REVIEW

Since the 1980s, numerous studies have analyzed the dependence and pattern of co-movement between stock exchanges around the world. They began to test various statistical and econophysics methods, however, the first stream of literature influenced by Geweke (1977) sought to analyze the dynamics of this co-movement by verifying the correlation between the different markets, according to Furstenberg et al. (1989), Bertero and Mayer (1990), Hamao, Masulis and Ng (1990), Ng, Engle and Rothschild (1992) and Cheung and Ng (1993).

The literature evolved towards the idea of finding a solution based on a model with factors. More specifically, a factor or factors that seek to reduce the set of information to a common source of variation among them. In general, this common source of variation is unobservable, and called unobserved latent factors. In this context, the objective is to use a set of variables related to this source and, by extracting the common variation component between them, obtain an approximation of this unobservable source. This current analysis and literature appeared in research on the search for common stochastic trends and verification of the transmission of shocks between markets, Johansen (1988), Blackman, Holden and Thomas (1994), Masih and Masih (1997) and Eun and Shim (1989), who presented evidence of a

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common stochastic trend between stock markets in developed and developing countries.

The DFM is used for the analysis and comparison of economic activity Nowcasting (2007), Giannone, Reichlin, and Small (2008b), and forecast modeling, since Sargent, Sims, et al. (1977) dynamic factor analyses are capable of explaining variables such as GDP, unemployment, prices, among others. With DFM it is possible to monitor the evolution of economic activity, with the premise that we know that a series of variables are affected or affect economic activity, although in possibly different directions and magnitudes. The principle of analysis is to extract the common variation component between these variables, in the present study, these variables are the Real Estate Funds available on the market and thus identify the influence of economic variables on the dynamics of co-movements.

Stimulated by this idea, this research seeks to carry out a forecast analysis for Real Estate Funds. With this objective and assistance from the literature for this problem, it may then be possible to gather this information, extract factors, and obtain predictions. Initially, the funds themselves will be used to carry out the analysis, and then macroeconomic variables will be inserted, such as inflation measures, economic activity, and agent confidence, using the Principal Components method (PCM).

2.1 REAL ESTATE INVESTMENT FUNDS

The Real Estate Investment Fund obtained its normative process published from Law 8,668 of June 1993 (Law No. 8,668/93), which established Real Estate Investment Funds (FII), without legal personality, characterized by the pooling of resources raised through the Securities Distribution System, by Law No. 6,385/76, intended for application in real estate projects.

According to Carvalho (2019), although real estate funds were created in 1993, it was in 2008 that real estate funds gained popularity in the national market. Until 2010, funds in this financial asset class had just over 10 thousand investors. In the first three years of the period analyzed, we observed strong growth in this number. In 2012, the total number of investors jumped from 40 thousand at the beginning of the year to approximately 100 thousand.

According to the report called Monthly Real Estate Funds Bulletin, issued by Brasil Bolsa Balcão (B3), base date December/2020, the total number of Funds

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registered with the CVM was 537, of which 301 were listed, with a PL of R$124 billion. The number of investors in the Brazilian market increased from 645 thousand investors to 1.172 million investors.

According to information and research from B3, it was identified that more than 1.16 million investors are Individuals, and in 2020, the total volume traded on the stock exchange was R$53.9 billion, with the average daily movement being R$216 million. Starting to offer attractive volumes of daily liquidity for large investors and institutional investors, such as pension funds, which began to adopt the class of Real Estate Funds in their investment portfolios, to increase the possibilities of allocation in assets that exceed their actuarial targets, given a scenario of low interest rates, which made traditional investments in fixed income unfeasible. Finally, it is observed that FIIs are beginning to be used to calibrate risk and return on investment portfolios.

2.2 DFM WITH PRICE AND ASSET RETURN SERIES

The analysis of price and asset return series is also carried out using the Dynamic Factor Model (DFM). Some authors have incorporated evidence from this research, such as Ng, Engle, and Rothschild (1992) Cheung and Ng (1993), Forni et al. (2000), Pagan and Soydemir (2000), Rocha and Sekkel (2006), Tabak and Lima (2013), Focardi, Fabozzi and Mitov (2016) and Conceição (2017). In addition to evaluating economies and their economic activities, the DFM is used in several models of integration and dependence between asset return series.

The main works developed new approaches based on the DFM framework, for example, Ng, Engle, and Rothschild (1992) define dynamic and static factors of excess returns on financial assets. Furthermore, they examine the value-weighted market portfolio as a dynamic factor and propose a procedure for searching for more dynamic factors.

In the same line of analysis, Cheung and Ng (1993) evaluate the importance of news from one country in generating volatility in the stock market of another country. In the analysis of interactions between the S&P 500 and Nikkei 225 indices in the pre and post-crash periods. The evidence presented the contribution of US news in generating volatility in Tokyo market shares, showing that there are dynamic factors and they spread throughout the world economy.

In the work of Forni et al. (2000), the authors propose a factor model with infinite dynamics and non-orthogonal idiosyncratic components. The model was new to the literature and generalizes the approximate static factor model of Chamberlain and Rothschild (1983), as well as the exact factor model à la Sargent, Sims et al. (1977). The unprecedented study also proposes an estimator of common components and presents simulation results.

Another important work is that of authors Pagan and Soydemir (2000) who use a VAR (Vector Auto-Regressive) model to analyze the extent of interdependence of stock markets in Latin America. The results of estimating impulse response functions suggest that there are strong links between the stock markets of Mexico and the US, and weaker but significant links between the stock markets of Argentina, Brazil, and Chile. In the same line of analysis, Rocha and Sekkel (2006) applied the model by Forni et al. (2000) for 24 different stock markets.

Complementing studies with various economies, but using asset markets, Tabak and Lima (2013) analyzed the causality and cointegration relationships between the stock markets of Latin America and the United States. In a simple framework, causality and cointegration are tested for Argentina, Brazil, Chile, Colombia, Mexico, Peru, Venezuela, and the United States. The authors found no evidence of cointegration between these stock markets, but short-term causality could not be rejected. For Brazil, Felício and Júnior (2014) examined the usefulness of factor models in analyzing the dynamics of the Real/Dollar exchange rate.

Focardi, Fabozzi, and Mitov (2016) presented a new statistical arbitrage strategy based on dynamic factor pricing models. The authors explored the mean reversion properties of prices reported in the literature. To empirically test the relative performance of return- and price-based models, they constructed portfolios (long-short, long-only, and equally weighted) based on predictions generated by two dynamic factor models.

Using the shares of companies included in the S&P 500 index to construct portfolios, the main results showed that prices allow significantly more accurate predictions than returns and pass the statistical arbitrage test. Using data from IBOVESPA, Conceição (2017) used dynamic factor models for the financial market based on stock prices, based on Stock and Watson (2016) and Focardi, Fabozzi, and Mitov (2016). For the author, when using the predictions made by the models, it is possible to create trading strategies whose performance can be measured, based on the closing prices of assets belonging to the IBX100 in the period from 2010 to 2016.

Most of the studies researched so far used principal components analysis - PCA to estimate the common factor. Chamberlain and Rothschild (1983) suggested using PCA to estimate the approximate static factor model, and Stock and Watson (1988); Stock and Watson (2002), and Bai and Ng (2002) popularized this approach in macroeconometrics. Two of the main tasks that researchers face when dealing with DFM are estimating the number of common factors as well as estimating the latent factors. Some well-known references on the consistency of the Principal Component estimator are Connor and Korajczyk (1986), Forni and Reichlin (1998), Forni et al. (2000), Bai (2003), Bai and Ng (2006) and Stock and Watson (2011).

Soto (2016) and Conceição (2017) used dynamic factor modeling and PCA to define common factors in the Brazilian stock market, Carvalho (2019) modeled and analyzed factors for the IFIX index. Therefore, the present work intends to carry out a more disaggregated analysis, with several real estate funds, and this modeling has not yet been explored, thus being the contribution of this work.

3 METHODOLOGY

3.1 DATA

The data comprises the monthly closing values of the shares of seventy-eight Real Estate Funds traded on the Brazilian stock exchange (B3) from 2013 to 2019. To analyze the relationship between the Main Factors (PCA) and economic and financial market variables, the indicators considered are IFIX - Real Estate Fund Index, IPCA - Broad Consumer Price Index, IGPM - General Price Index, Exchange rate (Dollar), NTN-B - National Treasury Notes type B and IMA-B - Anbima indicator that represents the performance of a portfolio of federal public securities.

In addition to these, the IBOV - the Bovespa index, IVG-R - Index of Guarantee Values of Financed Residential Properties, MVG-R - Median of Guarantee Values of Financed Residential Properties, and Fipe (Fipezap) which are real estate prices are also used. The variables are transformed into log returns, as data normalization can

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improve the estimates made. The equation of log-return (r) is $r = ln(1 + R)$, where *R* is the linear return and *ln* is the natural logarithmic.

3.2 DYNAMIC FACTOR MODEL (DFM)

The main idea of DFM is that the co-movements of an N-dimensional time series vector y_t can be explained by the sum of two mutually orthogonal unobserved components: the common component that has a pervasive effect on all variables in y_t, and the idiosyncratic component or noise, which is specific to each time series variable.

These models distinguish two representations in terms of the dynamic behavior of latent common factors. The Dynamic Factors model was originally proposed by Geweke (1977) and Sargent, Sims et al. (1977), and the standard representation, which is known as static or stacked representation, introduces the latent factors f_t, which is represented in Equation 1 contemporaneously, and the dynamic representation that takes into account the current effect, as well as the lags of the common factors Stock and Watson (2016).

According to Stock and Watson (2016), the co-movements of an N-dimensional vector of time series variables, y_t, are explained by the sum of two latent components: Λf_t and e_t, where Λf_t is the common component, f_t is a vector $r \times 1$ of common factors, Λ is a matrix $N \times r$ of factor loadings, and e_t, is the idiosyncratic component, a vector $N \times 1$ of idiosyncratic disturbances or errors.

Furthermore, factors follow time series processes, which have generally been assumed to be vector autoregression, VAR(*p*), where p is the degree of the polynomial matrix $\Phi(L) = (I \ - \ \phi 1 \ L - \ldots - \phi p \ Lp)$ (Forni et al., 2000). Where, η_t is a vector *r* × 1 Gaussian white noise with matrix P_η of positive and finite covariance, which is independent of the idiosyncratic error e_t, i.e., $Ee_t\eta_{t-k} = 0$ for all k.

$$y_t \ = \ \Lambda f_t \ + \ e_t \tag{1}$$

$$\Phi(L) f_t \ = \ \eta_t \tag{2}$$

The Equation (1) must be estimated with the information contained in the vector *N*-dimensional y_t. It is important to consider the following general assumptions about the factors f_t, the loading factor in the matrix Λ, and idiosyncratic errors e_t, following Stock and Watson (2002).

To avoid the identification problem, given that for any non-singular matrix A, $\Lambda f_t = \Lambda AA-1f_t$, it is assumed that: $E(f_tf_t) = P_{ff}$, where P_{ff} is a diagonal matrix with elements $\sigma_{ii} > \sigma_{ij} > 0$ for $i < j$, which means that factors may exhibit autocorrelation.

Factors will be identified up to a sign change given that matrix *A* is restricted to be diagonal with elements of ± 1. This format is most recommended for using principal component analysis. It is assumed that the series e_t and η_t are not correlated at any lag (lag used for forecasting), i.e., $E[e_t\eta_t - k] = 0$ for all k, and $E[e_te_t - k] = 0$ for all k. For the case of non-stationary series, Navarro and Rivera (2018) show that the model described by Equations 1 and 2 can be used with a series of log returns and log prices, which is weakly stationary.

In this context, the next section presents the PCA estimator, whose applications are found in Bai and Ng (2008) when considering multidimensional stochastic processes with a large number of observations, among them, obtaining common trends, which would be a reinterpretation of data to identify general patterns (Conceição, 2017).

3.3 PRINCIPAL COMPONENT ANALYSIS - PCA

The aim is to estimate the number of common factors *r*, as well as to estimate the factor loading space $M(\Lambda)$ and common latent factors f_t. In the present analysis, the interest is in estimating the common component and it is assumed that the number of common factors r is known. Specifically, we pay attention to one of the most applied methodologies in dimension reduction problems, Principal Component Analysis (PCA). Some well-known references on the consistency of Principal Component estimators are Forni and Reichlin (1998), Forni et al. (2000), Bai (2003) Bai, and Ng (2006).

Stock and Watson (2011) summarize the different methodologies within the time domain estimation of DFM in three generations. The first generation applied Gaussian Maximum Likelihood (MLE) and the Kalman filter to estimate low-dimensional parametric models. The second generation considered cross-sectional averaging methods to estimate high-dimensional non-parametric models. The third generation combines both models, using the consistent non-parametric factor estimates (second generation) in the state space model estimation (first generation), obtaining the parameter estimates.

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In this work, we follow the cross-sectional average methods, the vector f_t is considered an r-dimensional parameter to be estimated using the cross-sectional average of y_t. Therefore, the estimator f_t, f_t, is obtained as the weighted average of y_t using a non-random matrix of weights W, which is normalized so that $\frac{WW'}{N} = Ir$. The principal component estimator defines $W = \hat{\Lambda}$, where $\hat{\Lambda}$ is the matrix of scaled eigenvectors associated with the *r* largest eigenvalues of the sample covariance matrix *M* described below, and the factors are calculated as $\hat{f}_t = \widehat{\Lambda^J} y_t$, the first r scaled principal components of y_t and this estimator is consistent under the general error structure as shown in Stock and Watson (2011).

Following Bai and Ng (2002) and Conceição (2017), we chose the ICP2 criterion, as, according to the authors, it is suitable for the data format used in this research. The proposal by Pena and Box (1987) provides the most accurate estimate of $\hat{\Lambda}$, in terms of sample size T, time series dimension N, as well as the number of lags k_0 considering the function $V(k, F^k)$ specified in Equation 3.

$$V(k, F^k) = \min_{\Lambda} \frac{1}{NT} \sum_{i=1}^{N} \sum_{t=1}^{T} \left(X_{it} - \lambda^k F_{i\ t}^{k} \right)^2 \tag{3}$$

where, k is the number of factors. For a given k there are multiple solutions to this problem, and regardless of the normalization chosen, the value of $V(k, F^k)$ remains the same. With this calculated value, the ICP2 criterion is determined by:

$$ICP2(2) = \log\left(V(k, F^k)\right) + k \left(\frac{N+T}{NT}\right) \log\left(C_{NT}^2\right) \tag{4}$$

with $C_{NT}^2 = log(min(N, T))$. The number of factors chosen by the ICP2 criterion is a k such that the function $V(k, F^k)$ has the lowest value. According to Conceição (2017) based on the analysis of Connor and Korajczyk (1986), the dynamics of the factors, described in Equation 2, is a VAR(p) process, whose number of lags p can be estimated using the information criteria Akaike (AIC) and Bayesian (BIC), based on the following equations:

$$AIC = 2k - log\hat{L} \tag{5}$$

and

$$BIC = klogN - 2log\hat{L} \tag{6}$$

where $\hat{L}$ is the chosen maximum likelihood function. In the case of Conceição (2017), the estimated lag value was $p = 1$.

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3.3.1 Determination of Factors

To develop the principal components analysis and estimate the common factor, PCA was used, as the Factor Index - CI analysis.

$$IC_r = \ln\left(V(r, F')\right) + r\left(\frac{N+T}{NT}\right)\ln\left(\frac{NT}{N+T}\right) \tag{7}$$

Where $V(r, F^r)$ is the sum of squared residuals when r factors are estimated using principal components, following Bai and Ng (2007).

3.2.1 Comparison metric for forecasting models

Using the Mean Absolute Error (MAE) as a basis for comparison, which considers the analogous expression of the average simulation error with the absolute values as in the equation:

$$MAE = \frac{1}{T}\sum_{t=1}^{T}|Y_t^s - Y_L^a| \tag{8}$$

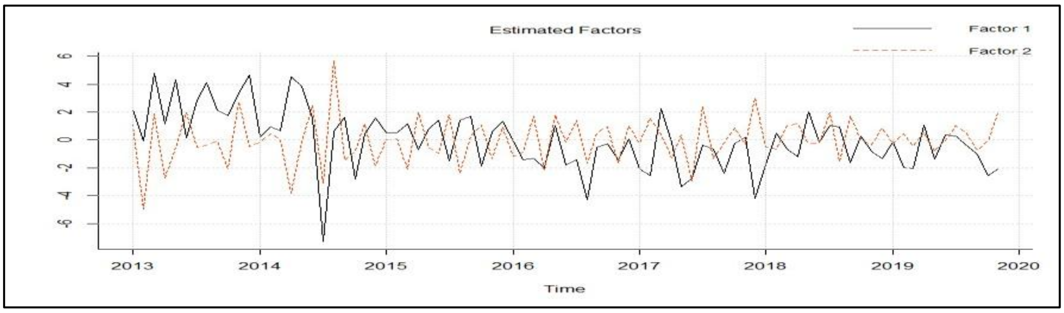
where, the low values of the measurements, inform the smallest error and the best model, when compared to the Y_t^s simulated, about the observed value of Y_t, what is Y_L^a.

4. RESULTS

4.1 COMMON FACTORS

The common factors are obtained through PCA and CI, which presented identical results regardless of the method used to identify the factors. Figure 1 shows the trajectories of the factors.

Figure 1. Factor Trajectories



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Source: Elaborated by authors.

The trajectory of the factors shows the volatility of Real Estate Investment Funds - FIIs, highlighting a high drop in 2014 with the economic crisis, then in 2016 with the impeachment process, and in 2017 with results below expectations for the economy. In 2018 there was an increase and a less volatile behavior at the end of 2019. Table 2 presents the results of estimating the factors using Principal Component Analysis - PCA.

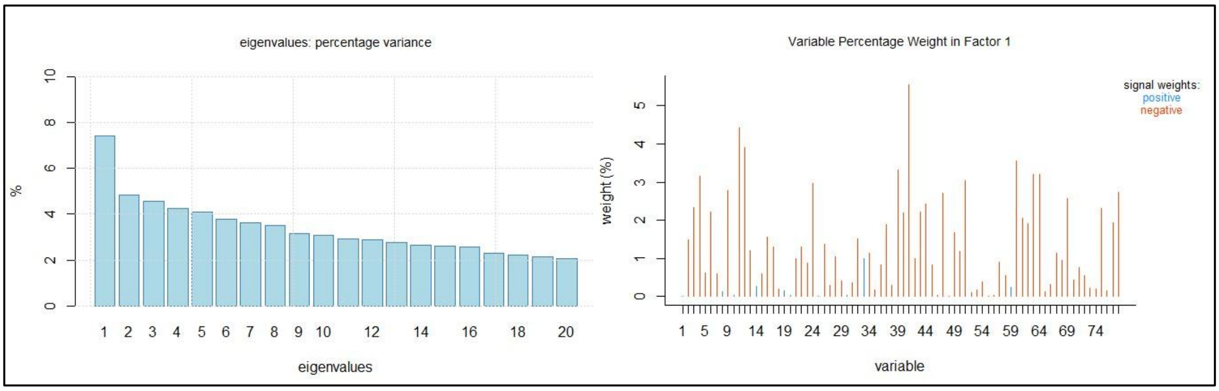
Table 2 –PCA Results

	PC1	PC2	PC3	PC4	PC5
Std. Deviation	0.04808	0.04302	0.04086	0.03944	0.03899
Proportion of Variance	0.07756	0.06211	0.05603	0.05218	0.05100
Cumulative Proportion	0.07756	0.13966	0.19569	0.24787	0.29887

Source: Elaborated by authors.

For Principal Component Analysis - PCA, the first four factors together explain approximately 24.78% of the variability in the data, with the four factors explaining, respectively, 7.75%, 13.96%, 19.56%, and 24.78% of the variability in the data. Analysis of the number of factors with the Factor Index - CI pointed out the first component. The result of the number of factors with the Factor Index is presented in Figure 2.

Figure 2. Percentage of Variance



Source: Elaborated by authors.

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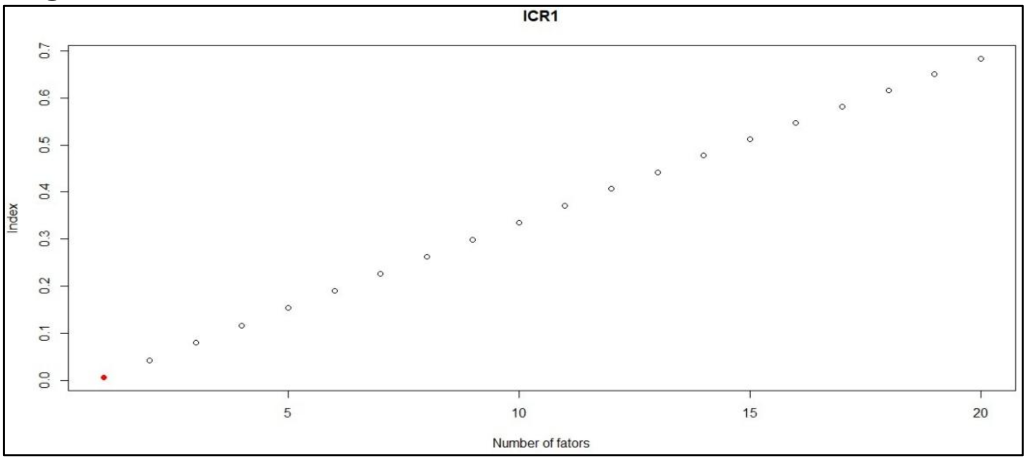
With the estimated factors, the model selects the parameters according to the number r of dynamic factors, the lag order of the factors p, and the number q of shocks to the factors. These parameters were defined by the algorithm according to Giannone, Reichlin, and Small (2008a) and Mariano and Murasawa (2003), who defined $r = 2$, $p = 2$, and $q = 2$. As the two methodologies (PCA and IC) are similar in the construction of the analysis to identify co-movements between financial series returns, the results support new studies and new comparisons. You can view the components in Figure 3.

Figure 3. Estimated Factor Index



Source: Elaborated by authors.

The empirical literature identifies different variables correlated with common factors that have an impact on economic variables, however, there are few studies relating to Investment Funds, and especially Real Estate Funds. Due to this gap in the literature, we estimated different models, with macroeconomic variables and financial market variables, to explore new results and new research frontiers.

4.2 MODEL ESTIMATION

4.2.1 Empirical Results of Model 1

Model 1 was estimated by OLS and its equation is characterized by:

$$y_t = \mu + \Lambda x_t + e_t \tag{9}$$

where the dependent variable y_t is Factor 1 in the first estimation and Factor 2 in the second estimation, the μ is the intercept, x_t the explanatory variables, and e_t the

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idiosyncratic error. The explanatory variables are IFIX, IBOV, IPCA, IGPM, Exchange Rate, NTN, and IMAB, which are extensively used in the specific literature.

This estimation allows us to analyze whether the two main common factors, that is, the co-movements extracted from the 78 FIIs, are influenced by the log-return dynamics of the explanatory variables. This research innovates by including economic and financial variables in the analysis, to explore these new results and mainly test the model of dynamic factors. The estimation results are in Table 3, which presents the model with Factor 1 and the model with Factor 2.

Table 3. Model 1 Results

Variables	Factor 1	p-value	Factor 2	p-value
(Intercept)	0.3862	0.0834.	-0.0713	0.7214
IFIX	-28.548	0.0014**	6.21787	0.4276
IBOV	0.6641	0.8963	-1.1255	0.8074
IPCA	-0.5319	0.0090**	-0.1668	0.3560
IGPM	0.3120	0.1046	-0.1545	0.3719
Exchange	-15.312	0.0142*	2.90535	0.6006
NTN-B	15.1333	0.0024**	1.62930	0.7098
IMA-B	3.7982	0.0419*	-4.1118	0.0156*
R-squared	0.3544		0.1054	
P-value	0.0000		0.2808	
P-value	0 '***'	0.001 '**'	0.01 '*'	0.05 '.'

Source: Elaborated by authors.

The effects on the first factor (Factor 1) showed promising results, some intuitive and others counter-intuitive. The results indicate that there is a statistically significant effect for IFIX, IPCA, Exchange, NTN-B, and IMA-B, however, for IFIX the sign of the coefficient was negative, which represents that the marginal increase in IFIX implies a linear decrease in Common Dynamic Factor 1. The IPCA and Exchange Indices also showed the same negative dynamics as the IFIX, which may determine that price and dollar increases negatively influence FIIs' returns.

For financial market indices such as NTN-B and IMA-B, the coefficients were positive and significant, being responsible for marginal increases in FIIs as a result of positive results in these indices. The model with Factor 1 as the dependent variable presented a significant p-value at 0.000 and R2 (R-squared) with an adjustment of 0.3544, the results are in Table 3.

For Factor 2, the only index that had a significant effect was IMA-B, resulting in secondary and marginal effects of IMA-B on the dynamics of FIIs, however, the coefficient was negative, empirically showing that IMA-B has variation negative over time. The other variables all had a p-value greater than 0.5%.

The estimation of the model with Factor 2 as the dependent variable presented a p-value of 0.2808 and R2 with an adjustment of 0.1054, respectively a result without statistical significance and low adjustment, indicating evidence that the idiosyncratic effects, that is, the error measured by et carries the most of the model explanation.

4.2.2 Empirical Results of Model 2

For a specific analysis of the Real Estate Fund Market, the initial database of 78 FIIs was divided into Brick and Paper FIIs. Brick funds are represented by physical properties: stores and supermarkets; Bank agencies; shopping malls; and sheds. On the other hand, receivables or paper funds are made up of bonds or securities linked to the real estate sector.

Of the 78 selected FIIs that remained in the sample, 62 FIIs have a Brick specification and 16 have a Paper specification. With these two new samples, estimations were carried out via OLS to evaluate the impact of economic and financial variables, and the real estate market price indices were also included. The principal components analysis was estimated separately for Brick and Paper FIIs, the results are presented in Tables 4 and 5.

Table 4 – PCA Results - Brick FIIs

	PC1	PC2	PC3	PC4	PC5
Std. Deviation	0.04686	0.04124	0.03898	0.03780	0.03672
Proportion of Variance	0.08726	0.06761	0.06040	0.05678	0.05360
Cumulative Proportion	0.08726	0.15487	0.21527	0.27205	0.32565

Source: Elaborated by authors.

For the estimated factors of Brick FIIs, the cumulative variation of factors PC1 to PC4 was 27.20% of the factors in the database, being: 8.72%, 15.48%, 21.52%, and 27.20%.

Table 5 – PCA Results - Paper FIIs

	PC1	PC2	PC3	PC4	PC5
Std. Deviation	0.0301	0.0273	0.0248	0.02266	0.02012
Proportion of Variance	0.1951	0.15974	0.1324	0.11058	0.08719
Cumulative Proportion	0.1951	0.35488	0.4873	0.59788	0.68508

Source: Elaborated by authors.

In the case of data from FIIs characterized as paper, the cumulative proportional variation of common factors had PC1 with 19.51%, PC2 with 35.48%, 48.73%, and 59.78% for PC3 and PC4 respectively of the sample factors. The division between Brick and Paper FIIs showed interesting and complementary results of the total factors, which represents real differences in the dynamics of FIIs with different market characteristics.

According to research by Oliveira and Milani (2020), the Ibovespa Index was the only variable that explains the return of Real Estate Funds. In this study, the authors used several macroeconomic and market indices. The article by Haas et al. (2021) also corroborates this research and concludes that it is not trivial to understand the factors that caused the FIIs' value portfolio. In this context, Moraes and Serra (2017) concluded that larger funds are more diversified. The number of properties and the concentration of properties were not significant in explaining the diversification of FIIs.

The aforementioned works took into account market indices to measure the effects of FIIs, to understand these effects the following indices were incorporated: IVG-R - Index of Guarantee Values of Financed Residential Properties, MVG-R - Median of Guarantee Values of Residential Properties Financed and the Fipezap Price Index, to understand how economic and financial variables and market indices influence the common dynamic factors of Brick and Paper FIIs. The results of estimating the model with Common Factors for Brick FIIs are presented in Table 6.

Table 6 – Results of Model 2 - FII Tijolo

Variables	Factor 1	p-value	Factor 2	p-value
(Intercept)	-0.3829	0.17643	0.1196	0.673
IFIX	-23.2572	0.00477**	6.2091	0.442
IBOV	-1.3604	0.77389	-0.6817	0.886
IPCA	-0.4603	0.01320*	-0.1838	0.317

IGPM	0.3130	0.08076.	-0.1744	0.330
Exchange	-14.5436	0.01125*	3.3373	0.555
NTN	11.1141	0.01947*	2.4889	0.596
IMAB	2.2782	0.20040	-3.8558	0.033*
IVG	162.0199	0.00616**	11.0655	0.849
MVG	10.4174	0.23018	-4.1484	0.633
Fipe	-135.6645	0.01735*	61.4695	0.276
R-squared	0.4879		0.1612	
P-value	0.0000		0.2053	
P-value	0 '***'	0.001 '**'	0.01 '*'	0.05 '.'

Source: Elaborated by authors.

The empirical evidence from the model with brick FIIs and incorporating the Real Estate Market Indices presented new results, where the IFIX in Factor 1 was significant with a negative coefficient, and for Factor 2 the IFIX was not significant. Other statistically significant indices for Factor 1 were the IPCA, the Exchange rate, and the NTN, but with a negative marginal effect.

The IMAB Index was significant in Factor 2 and had a negative coefficient. For the newly incorporated indices, IVG, MVG, and Fipe, the results showed that these variables were significant for IVG and Fipe, and MVG had no significant effect. The IVG was positive, which shows its influence on the common factors of Brick FIIs, and the Fipe Index was negative in this segment of the FII. The model had a better fit than the previous model with R2 of 0.4879 in Factor 1 and 0.1612 in Factor 2. The factors continue, with a strong effect given by idiosyncratic components.

4.2.3 Model 3 Empirical Results

Paper funds are made up of bonds or securities linked to the real estate sector, the sample analyzed contains 16 real estate funds - FIIs in the period from 2013 to 2019. The funds characterized as paper had their common factors estimated by the OLS model:

$$y_t = \mu + \Lambda x_t + e_t \qquad (10)$$

where y_t are the common factors extracted from paper FIIs, μ the intercept of equation Λx_t characterizes the dependent variables that are formed by IFIX, IBOV,

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IPCA, IGPM, Exchange, NTN, IMAB, IVG, MVG, and Fipe (Fipezap), and e_t is an error term.

Table 7 presents the result of the OLS estimation of Common Factors 1 and 2. For IFIX, the result remains similar to the model results 1 and 2, with a negative and statistically significant coefficient, which appears to be unintuitive, as a marginal increase in the IFIX index would decrease common factors, that is, the behavior of paper FII funds would fall.

In this sample, marginal increases in the IPCA, exchange rate, and Fipe would also contribute to reducing the returns of paper FIIs. The variables that have a positive impact and are statistically significant are the NTN and IVG, financial market indices that can be predictors for FIIs.

The model estimated with Factor 2 did not show statistical relevance in any variable, and the model for Factor 1 presented an adjustment with R2 (R-squared) of 0.4759, that is, the variables used in the analysis explain 47.59% of the behavior of movements of paper FIIs. Many other elements explain the dynamics of paper FIIs over time.

Table 7 – Results of Model 3 - FII Paper

Variables	Factor 1	p-value	Factor 2	p-value
(Intercept)	-0.2567	0.31779	-0.03911	0.812
IFIX	-21.0862	0.00491**	-6.51296	0.167
IBOV	-1.7698	0.68136	-3.88580	0.163
IPCA	-0.4165	0.01370*	-0.10549	0.322
IGPM	0.2404	0.13917	0.08566	0.409
Exchange	-13.7536	0.00854**	-4.75914	0.149
NTN	11.5773	0.00783**	-0.41436	0.879
IMAB	2.2807	0.15944	0.18789	0.856
IVG	123.8897	0.02039*	21.21125	0.529
MVG	7.3611	0.35049	5.97448	0.239
Fipe	-110.5114	0.03251*	32.95702	0.315
R-squared	0.4759		0.1612	
P-value	0.0000		0.2053	
P-value	0 ‘***’	0.001 ‘**’	0.01 ‘*’	0.05 ‘.’

Source: Elaborated by authors.

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Economic activity involves a series of variables that come together to explain the dynamics of the economy, the results found in the research show that the movements of FIIs are not easily represented by economic variables or market indices, the literature already indicates that this dynamic is complex and there are other determinants.

The main indicator of the FII market is the IFIX, and in the three estimated models, the IFIX was significant, however, its marginal effect was negative, an unintuitive result. In the work of Oliveira and Milani (2020), the IFIX variable was used as a dependent, and even in this context the results also observe contradictions. For IFIX, the study by Carvalho (2019) modeled the forecast in three different equations, achieving good results for forecasting. Other studies that used IFIX and other real estate market indices were by Oliveira and Milani (2020), Haas et al. (2021), and Moraes and Serra (2017) which corroborate the complexity of the results of this research, as they show that not all factors influence FIIs.

For the inflation rate Giannone, Reichlin, and Small (2008a) also present a series of variables to estimate the factors and test their influence on price behavior. For FIIs, whether the complete set of data or separated into Brick and Paper, the Price Index measured by the IPCA was significant in the three models, however, its effect is negative for FIIs, that is, a marginal increase reduces the factors common factors that determine FII returns.

For the case of the dollar, Felício and Júnior (2014) used the common factors of the exchange rates of a set of countries with macroeconomic variables. These factors of the rates of other countries are determinants of the national rate. In the case of FIIs, the exchange rate measured by the real/dollar ratio had a significant effect on the common factors for the three estimated FII models, and its marginal effect was negative, which is intuitive when thinking that the dollar is also a competing investment to the FII.

The NTN, IMAB, IVG, and Fipe indices presented statistically significant results, for NTN the marginal effect was always positive in the three estimated models, IMAB only for model 1, IVG for models 2 and 3, and Fipe had a negative effect marginally. These market indices were used by Oliveira and Milani (2020) and Haas et al. (2021) and their significant and positive results corroborate those presented in this research. The study by Conceição (2017) for the stock market using IBOVESPA and the

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estimated factors of the IBX-100 were positive and significant, in the present analysis IBOVESPA did not present a statistical effect in any of the models.

5 FINAL CONSIDERATIONS

The present work sought to analyze the dynamic factors of Real Estate Investment Funds listed on the Brazilian stock exchange by correlating them with economic variables and real estate market indices through common dynamic factors. The results indicate that most of the returns are given by idiosyncratic components, that the estimated factors of FIIs are complex, and that there are a variety of indicators that reflect this market.

Market indicators such as IFIX, IVG-R, NTN-B, IMAB, and Fipe have effects on the common factors of FIIs, and the IPCA and Exchange variables also impact the dynamics of the funds, whether in the analyzed set or the brick sample. or paper. In general, the results conclude that the dynamic factors methodology to measure the co-movements of Real Estate Funds presented promising results. There are differences between the samples analyzed, whether by the set of 78 funds or, in brick and paper, which can influence the predictive dynamics.

This result corroborates the empirical literature, as it confirms the existence of unobservable factors extracted from real estate investment funds, and that their co-movements are complex, with a variety of unobservable dynamics that influence their behavior. Thus, this work was the one that most explored models to identify whether economic and market variables have a marginal effect on the factors or co-movements of Brazilian securities investment funds.

The methodological process of exploring new empirical results presented promising considerations, whether by using a new package developed by Brazilians to estimate the nowcast of macroeconomic variables in any temporal format, or by understanding that the common dynamic factors related to Real Estate Investment Funds are complex and that there are a variety of unobservable dynamics that influence their behavior.

It brought as a novelty a more specific analysis of the common dynamic factors of Brick and Paper SIEFs, with promising results regarding predictors such as the NTN-B Index, IMA-B, IVG, and Fipezap. The results present greater explanatory power of

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the main components when applied to paper funds, vis-à-vis brick ones, and when applied to paper funds the explanatory power is practically doubled.

As a suggestion for future research, it could be verified whether there is a long-term balance between the performance of market indices and real estate investment funds through cointegration and error correction models.

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