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Factorial asset pricing models using statistical anomalies☆

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ABSTRACT

Although up to seven factors market, size, earnings, profitability, investment, momentum, and quality are used to explain asset returns mainly due to anomalies, there is no consensus in the financial literature on the suitability of the factors to include in asset pricing models. Empirical research has found that investors' responses to market movements up and down are not symmetric. We show a new type of anomaly, statistical anomalies, resulting from decomposing asset returns into three independent time series: positive outliers (the good), negative outliers (the bad), and the remainder or Gaussian returns (the usual). Using a sample consisting of 49 equal-weighted US industrial portfolios with daily and monthly frequencies from 1969 to 2020, we find evidence that the good-usual-bad factor model exhibits fewer anomalies, better explanatory power, and greater robustness than the "magnificent seven" factors model. Our results are relevant to investors trading at less than monthly frequencies.

1. Introduction

Markowitz (1952) changed the rule of asset selection and showed the relations between expected returns and the variance of returns. One of Markowitz's important thoughts is that the law of large numbers applied to asset portfolios does not apply, because assets are correlated and therefore diversification does not remove all portfolio variance.

Subsequently, Sharpe (1964) provided the first theory relating to expected return and risk. Although it assumes that the outcome of any investment follows a probabilistic distribution, when it also assumes that the total utility function of investors depends on expected return and variance, then the set of possible probability distributions is limited to those that can be described by their first two statistical moments. Additionally, this theory implies that the asset pricing model is linear and that systematic risk arises for the non-diversifiable variance component identified by Markowitz (1952), which leads to a one-factor or market factor model. Black et al. (1972) thus find that the behavior of well-diversified portfolios is explained to a much greater extent by a model with two independent factors than by a single-factor or market model. So began the search for the explanatory factors of asset returns under the previous premises.

Black (1972) notes that the distribution of possible returns on an asset is likely to be closer to log-normal than normal and indicates that the normal (or log-normal) distribution is generally regarded as an acceptable approximation of reality. In addition, different lines of research on the financial valuation of assets are emerging. While empirical works on the pricing of derivatives usually consider variables such as the time structure of volatility (He and Chen, 2021; He and Lin, 2021), those focused on asset pricing (i.e., of the underlying assets in financial derivatives) analyze the explanatory factors of the behavior of excess returns. In this empirical study, we

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focus on this last approach, particularly the criticism related to the symmetrical response of factors to up and down movements, since the empirical evidence shows that investors are especially concerned about negative movements (stylized facts). Under this assumption, the returns do not follow a normal distribution, so that the probabilities of returns being above and below the mean are not the same. Basu (1997), using firms' stock returns to measure news, finds a systematic difference between periods of bad news and good news in the timeliness and persistence of earnings. In this regard, Campbell and Cochrane (1999) argue that, when the economy enters a recession, investors have fewer resources and are therefore less inclined to take financial risks. Additionally, Lettau and Ludvigson (2010) find that the Sharpe ratio increases substantially during recession periods. Therefore, this behavior is consistent with the conjecture that investors are more risk averse and therefore demand higher returns on the assets they hold in their portfolios during economic downturns. The financial literature has consequently considered this problem within the capital asset pricing model by including moments of higher order than the variance, with improved results compared to the traditional approach (Kraus and Litzenberger, 1976; Harvey and Siddique, 2000; Dittmar, 2002). Another solution to the problem was provided by Kahneman and Tversky (1979), using semi-variances, so that the traditional capital asset pricing model beta is replaced by two coefficients measuring the response of asset returns to up and down movements, respectively, in the market. Bawa and Lindenberg (1977), Kaplanski (2004), Post and van Vliet (2004), and Ang et al. (2006), for example, find empirical evidence favoring these two coefficients. In this context, our main contribution is to propose a new asset pricing model whose factors are these upward, downward, or normal movements and to prove that such a model is superior to the usual multifactor pricing model. Our study then focuses on anomalies and tries to identify a new type of factor, different from the usual seven factors, that allows for a reduction of the anomalies.

The financial literature has also proposed adding more factors to the explanatory model for asset returns. Fama and French (1992) propose a three-factor model (with market, size, and earnings–price factors) to explain asset returns. Their model has drawbacks, however, for firms that do not have December fiscal year-ends and requires 24–60 months of previous asset market returns for estimation. Fama and French (1993) subsequently defined and named the following three factors: the market factor (Mkt-Rf), or the excess return on the risk-free rate; the size factor, or firms' small minus big market returns (SMB), where size is measured by the book-to-market ratio; and the earnings–price ratio, or firms' high minus low market returns (HML), using the earnings–price and book-to-market ratios to classify the firms. Fama and French (1993) find that the explanatory power of the market factor model is 61–92% for the monthly excess return on the risk-free rate for 25 portfolios formed using size and the book-to-market ratio, compared to that for the three-factor model, which is 83–97%. We have two concerns, however, about these results: the data frequency and the criteria used to form the portfolios. The first concern, unlike higher observation frequencies (e.g., daily), guarantees that the assumptions about the normal distribution are met. The second concern is the potential for multicollinearity problems among the factors and endogeneity, since the portfolios and the factors are formed using the same criteria.

Jegadeesh and Titman (1993) defined a new asset return characteristic that shows the persistence of returns (momentum, or WML). Using this result, Carhart (1997) expanded the model to four factors – Mkt-Rf, SMB, HML, and WML – where WML is the difference between the portfolio returns formed by high-return assets (lags) and low-return assets. Using monthly data from mutual fund returns, Carhart (1997) found that the explanatory power of the four-factor model is 89–97%. The inclusion of the momentum factor has been highly relevant to financial empirical research and has even improved the explanatory power of cryptocurrency factor models (Jia et al., 2021).

Another advance in the search for the explanatory factors of asset returns was made by Fama and French (2015). Their proposal includes market, size, value, profitability, and investment patterns. Besides Mkt-Rf, SMB, and HML, Fama and French (2015) include the differences between the returns on diversified portfolios of stocks with robust and weak profitability (RMW) and for low-investment (conservative) and high-investment (aggressive) firms (CMA).

Finally, Asness et al. (2019) proposed a new asset characteristic, known as quality, and define it as profitability, growth, and good management. A new factor thus emerged, quality minus junk (QMJ), estimated as the difference of the portfolio returns formed with quality assets minus the portfolio returns of junk assets. The results show that a five-factor model explains only around 70% of the QMJ factor, so this factor could contain other unobserved information.

Seven factors (Mkt-Rf, SMB, HML, RMW, CMA, WML and QMJ), then, offer higher explanatory power for monthly data only, but they present potential endogeneity and multicollinearity problems. In this study, we call this set of factors the magnificent seven (M7). However, despite the number of factors considered, the results for the asset pricing factor model are inconclusive, since empirical research finds significant alpha (constant) values. These are known as anomalies (data that significantly affect market performance) that are not included in the factors (e.g., Calomiris et al., 2012; Hou et al., 2015; Fama and French, 2016; Stambaugh and Yuan, 2017).

Given the inconclusive results for the asset pricing factor model, much of the financial literature has been concerned with looking for other explanatory factors of asset returns through observable and unobservable variables. For example, Frazzini and Pedersen (2014) defined the betting against beta (BAB) factor to measure the difference between the returns of portfolios with high and low beta assets, and Nandha and Hammoudeh (2007) and Mohanty et al. (2011) proposed oil price as a new factor. The improvement of the model, however, is irrelevant, and these factors are not exempt from endogeneity or multicollinearity problems with respect to the market factor (Mkt-Rf) already considered. Furthermore, if we include new factors, we need more information, and then the likelihood of the factors being improperly built or of mispricing increases.

Thus far, financial research on asset pricing has identified different anomalies that we group as follows: calendar anomalies (Hansen and Lunde, 2003), fundamental anomalies (Basu, 1977; Banz, 1981; Cochrane, 1996; Hou et al., 2015; Fama and French, 2006; Chordia et al., 2008), and technical anomalies (Brock et al., 1972; Malkiel, 2003). Currently, we can include other types of anomalies resulting from the effects of the COVID-19 pandemic; for instance, Yuta and Sakamoto (2021) show that strengthening lockdown measures negatively impacts asset prices. However, Hou et al. (2020), replicating financial literature anomalies, find that most of them are nonsignificant at the conventional 5% level and conclude that the capital markets are more efficient than previously recognized. Again, there is no consensus on the anomalies.

Empirical research in the financial literature examines the effects of non-normal returns on asset pricing by analyzing the asymmetry and/or extreme values of the returns in reducing fundamental anomalies. Price et al. (1982) analyze positive and negative returns separately to study the asymmetry of systematic risk distinguishing between up and down market movements and find significant differences between measures of systematic risk assuming a log-normal distribution and using so-called semi-variances. The empirical results of Bali and Cakici (2004) show that average stock returns are not positively related to the market beta at the company level and that (extreme) value at risk can provide additional explanatory power, even given the usual risk factors. Bali et al. (2011) analyze the extreme asymmetry of returns by studying the significance of extreme positive returns (maximum daily returns over the past month) in the cross-sectional pricing of stocks and find that extreme positive returns explain the negative relation between returns and idiosyncratic volatility. Other investigations analyze the left tail of returns. Huang et al. (2012), for example, proposed a measure for extreme downside risk to investigate whether bearing such risk is rewarded by higher expected stock returns. They find that stocks with extremely high downside risk yield higher expected returns during periods when market returns are expected to be high, and that extremely low downside risk stocks underperform when the market is experiencing large drops, suggesting that extreme downside risk reflects certain fundamental components of risk. Zaremba (2019) uses the difference between previous maximum and minimum prices as a measure of country and industry risk and finds a strong positive relationship between the price range and future returns that is not explained by the usual factors of asset pricing. Umutlu and Bengitoz (2021) find that this price range (maximum and minimum) is a convenient measure of stock returns' total volatility.

However, considering only extreme values (maximum and minimum) ignores other characteristics of asset returns. Kelly and Jiang (2014) show that tail risk has strong predictive power for aggregate market returns and that the alphas of stocks with high loadings on past tail risk are higher than those of stocks with low tail risk loadings. Similarly, Bali et al. (2014) use covariance measured across the left tail of individual stock return distributions to estimate systematic risk and find a positive and significant relation between this covariance and expected stock returns. Considering only the (positive and negative) returns of the tail of the probability distribution, however, in addition to not considering other statistical properties of the returns (e.g., autoregressivity and heteroscedasticity) entails a certain degree of subjectivity in setting the percentile at which the tail of the distribution begins.

To achieve our goal of reducing anomalies, including asymmetry and extreme values of returns, we use the empirical evidence of González-Sánchez (2021), who finds a relationship between the scaling property of asset returns and outliers or shocks and shows that outliers imply rejection of the hypotheses of the absence of autocorrelation and heteroscedasticity. This result is relevant because the usual estimate using ordinary least squares (OLS) assumes that the error term is neither autocorrelated nor heteroscedastic, since the estimators are best linear unbiased estimators. However, if the residuals are heteroscedastic, then the estimators are no longer efficient, so the regression predictions will be inefficient too. Additionally, if the residuals are autoregressive, then the estimators will still be consistent but possibly biased. In short, it seems that outliers reveal information that is not captured by the usual factors and imply potential problems with the estimates.

To avoid subjective or excessively restrictive criteria, we apply the methodology of González-Sánchez (2021) in looking for outliers in the time series of asset returns, which are defined as statistical anomalies, and then build three new factors for each market asset or portfolio based on these, that is, for the positive outliers (the good), the negative outliers (the bad), and the remainder of the returns, or normal returns (the usual). Finally, we aim to analyze whether these statistical factors – good, usual, and bad (GUB) – are better able to explain the excess return of the assets and if they are more robust than the M7 factors.

The remainder of the study is organized as follows. Section 2 explains the methodology for testing the hypothesis. Section 3 examines the sample data. Section 4 analyzes the results. Finally, Section 5 discusses the results and draws our conclusions.

2. Methodology

First, we define the M7 factors model for each industrial portfolio and both daily and monthly frequencies as:

$$r_t = \alpha_0 + \sum_{j=1}^{J=7} \beta_j \cdot F_{j,t} + e_t \tag{1}$$

where r_t is the excess return on the risk-free rate of each industrial portfolio (at both frequencies), $F_{j,t}$ represents each factor of the M7, β_j is the industrial portfolio sensitivity for each factor, α is the intercept with the null expected value for the absence of anomalies, and e_t is the error term, or idiosyncratic risk. We estimate expression (1) using OLS and feasible generalized least squares (FGLS; see Harvey, 1990; Narayan and Liu, 2018). In addition, because of the statistical problems of the time series of asset returns, we estimate standard errors as robust against autoregression and heteroscedasticity (HAC; see Andrews, 1991). In addition, to measure the adjusted degree of the model, we use the individual statistical significance of the parameters and adjusted R^2 values. Finally, we apply the following tests (following Gibbons et al., 1989; Campbell and Thompson, 2008; Welch and Goyal, 2008; Phan et al., 2015; Fama and French, 2017; Barillas and Shanken, 2018; Narayan and Liu, 2018; Sha and Gao, 2019) to verify the robustness and performance of the estimated model for each portfolio.

- Alpha ratios: We estimate $\frac{\text{average}(\alpha_i^2)}{\text{average}(\bar{r}_i^2)}$ as the ratio of the unexplained dispersion of average excess returns to the total dispersion of average excess returns. The lower the ratio, then, the lower the intercept dispersion to the total dispersion. We also calculate the proportion of unexplained dispersion in the average excess returns attributable to sampling error as $\frac{\text{average}[s^2(\alpha_i)]}{\text{average}(\alpha_i^2)}$, where s^2 is the average of the squared sample standard errors of α_i. A low value for this ratio thus shows a low value in the dispersion of the intercepts due to sampling error rather than in the dispersion of the true intercepts.

- Additionally, R^2_{out} is the out-of-sample R^2, which is estimated as $R^2_{\text{out}} = 1 - \frac{\text{MSE}_{\text{out}}}{\text{MSE}_{\text{mean}}}$, where MSE_{out} is the mean squared error of the out-of-sample predictions from our proposed model and MSE_{mean} is the mean squared error of the historical sample mean. Therefore, if $R^2_{\text{out}} > 0$, then our proposed predictive regression model predicts returns better than the historical mean (Welch and Goyal, 2008). The expected R^2_{out} under the null hypothesis of unpredictability is negative (efficient market), a zero R^2_{out} can be interpreted as weak evidence for predictability, and a positive R^2_{out} implies an inefficient market.
- Finally, we estimate the Gibbons–Ross–Shanken (1989, GRS) test to confirm whether all alphas are jointly zero from a set of time series regressions.

To test the GUB model, we begin by building the factors, as follows:

1 In a first step, we divide the series of returns of each portfolio i into three subseries, for the positive outliers ($o_{i,+}$), for the negative outliers ($o_{i,-}$), and, finally, for the usual returns (u_i). While the first two involve extreme positive and negative movements, the last one is characterized by acceptance of the null hypotheses of the absence of non-normality, autocorrelation, and heteroscedasticity. For each industrial portfolio, we divide the excess return (daily and monthly) into three time series (positive outliers, negative outliers, and normal returns), where the sum of the three equals the original series. To do so, we select τ_n, τ_a, $\tau_{a,2}$, and τ_h as the tests of normality, autocorrelation, autocorrelation for the square of the data and heteroskedasticity, respectively. Then, we identify the outliers as follows:
   (a) For $t = 1$ to T and portfolio i, we search for $\max|r_{i,t}|$ or the highest absolute value of the entire time series.
   (b) Depending to the sign of these data, we include them in the positive ($o_{i,+}$) or negative ($o_{i,-}$) outlier series, while we replace this original return value with zero in the usual (u_i) time series. Note that this procedure makes all three series independent (for more details, see González-Sánchez, 2021).
   (c) After the replacement, we estimate the τ_n, τ_a, $\tau_{a,2}$, and τ_h tests for this new usual time series, and, if the hypotheses of normality, non-autocorrelation, and non-heteroskedasticity are accepted, we apply the same procedure to the next industrial portfolio, until we reach the last one.
   (d) Otherwise, we return to step (a) and repeat the procedure until the usual time series passes the tests for portfolio i.

2 Once the series of returns of all the portfolios has been divided into the three subseries ($o_{i,+}$, $o_{i,-}$, and u_i), in a second stage we then construct the GUB factors from these subseries. To do so, if T is the sample size for each estimate at the monthly or daily frequency of the GUB factor model, we build the GUB factors in matrix form as $A_{1,T} = w_{1,N} \cdot Z^A_{N,T}$, where $Z^A_{N,T}$ is a matrix of dimension NxT (with N the total number of portfolios) that includes for each industrial portfolio the positive outliers, or ($o_{i,+}$), when A is a good factor; the negative outliers, or negative ($o_{i,-}$), when A is the bad factor; and the normal returns, or the usual (u_i), when A is the usual factor, with $A_{1,T}$ a vector of dimension $1 \times T$ with the values G, U, or B resulting from the factors, respectively. Finally, $w_{1,N}$ is a vector of dimension $1 \times N$ of the weights for each industrial portfolio in each factor $A = \{G,U,B\}$, estimated for portfolio i for each estimate time T as $w_{i,T} = \frac{m_{i,T}}{\sum_{s=1}^{N} m_{s,T}}$, where m is the number of positive outliers for each portfolio i (when A is a good factor), negative outliers (when A is a bad factor), or the normal returns (when A is a usual factor), such that the sum of the m_i positive outliers, negative outliers, and usual returns equals the sample total T. In short, the vector of weights for each portfolio for each GUB factor equals the average percentage of outliers (positive or negative) or usual returns for each portfolio in the sample period with respect to the total number of portfolios.

Next, we estimate the GUB model for each industrial portfolio and both daily and monthly frequencies using the OLS and FGLS methodologies and HAC standard errors:

$$r_t = \alpha_0 + \beta_G \cdot G_t + \beta_U \cdot U_t + \beta_B \cdot B_t + \epsilon_t \tag{2}$$

Finally, we run the same robustness tests as for the M7 factors model.

3. Data

All data are freely available to facilitate the replication of this empirical study or to improve it. The values of the Fama–French factors (Mkt-Rf, SMB, HML, RMW, CMA, and WML) and portfolio returns, at both daily and monthly frequencies, can be consulted on French's data website,[1] and the QMJ factor values are obtained from the AQR Data website.[2]

Both the returns of the portfolios and the factors correspond to the US market over the periods from July 1, 1969, to June 30, 2020 (for daily frequencies) and from July 1969 to June 2020 (for monthly frequencies). We use industrial portfolios as assets to be valued, because the literature on multifactor asset pricing usually models these portfolios. In addition, empirical research shows the relevance

[1] See https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html.

[2] For monthly frequencies from https://www.aqr.com/Insights/Datasets/Quality-Minus-Junk-Factors-Monthly and for daily frequencies from https://www.aqr.com/Insights/Datasets/Quality-Minus-Junk-Factors-Daily.

of the industry factor as reflecting the particular characteristics of each sector as being either productive, systematic risk, or regarding the life cycle (Bekaert et al., 2011; Umutlu and Bengitoz, 2020). Since industry returns exhibit large cross-industry variation, this issue is particularly important in this study, since the high degree of cross-sectional variation in asset returns increases the power of asset-pricing tests.[3] The selection of the beginning of the period is subject to the availability of the returns of the portfolios chosen as the dependent variable. These portfolios are the 49 industrial portfolios that appear on French's data website, and the assets are equally weighted to avoid endogeneity problems in the case of weights based on size or performance. The dependent variable is the excess returns of the portfolios over the risk-free rate (daily or monthly, from *French's data website*).

Tables 1 and 2 show the main statistics of the excess return portfolios for daily and monthly frequencies, respectively. Note that, though autocorrelation and heteroscedasticity decrease with the data frequency, unlike individual returns on assets, it does not disappear in portfolios and even non-Gaussian behavior of return remains.

Table 3 shows a statistical summary of the factors for both daily and monthly frequencies. We observe that the factors present the same statistical characteristics as the industrial portfolios; therefore, by reducing the observation frequency, the property of time scaling is weaker than in individual assets. This could be because the interaction among assets in the same portfolio dilutes this property.

Additionally, Table 4 presents the correlations between the factors to verify possible multicollinearity problems. As shown, there are correlations that are higher than 0.4 and even 0.7. Note also that the correlations for the daily frequencies are higher than for the monthly frequencies.

In short, the portfolios show a weaker time scaling property, probably due to their construction, since their return is an average of their components' returns, as González-Sánchez (2021) points out. Furthermore, any estimate of an asset pricing model under these circumstances assumes that the standard errors of the estimated parameters should be robust for autocorrelation and heteroscedasticity (e.g., HAC). The residuals' behavior should also be analyzed to test if they meet these statistical requirements.

4. Results

The results are obtained for rolling regressions using samples of five years of data (T is 1250 daily observations or 60 monthly observations). For each industrial portfolio, 11,616 regressions are performed for the daily frequency and 553 regressions for the monthly frequency for both the M7 and GUB models. Additionally, the regressions are estimated by both OLS and FGLS. In summary and for the total of 49 portfolios, 2,276,736 regressions are performed for the daily frequency and 108,388 regressions for the monthly frequency.

4.1. Building GUB factors

Table 5 shows the average weights[4] for the good, bad, and usual factors for each industrial portfolio and frequency.

Note that the average weights for the usual factor are very similar to an equal-weighted portfolio (1/49 = 2.04%). On the contrary, the average weights for the good and bad factors are between 0.9% and 4.9% and between 0.8% and 4.4%, respectively, for the daily frequency and between 0.3% and 9.5% and between 0.3% and 6.4%, respectively, for the monthly frequency. Industrial portfolios are thus affected by the good and bad factors in different ways.

Additionally, Fig. 1 shows the industrial portfolio with the highest annual average weight for each GUB factor. Note that, for years of economic crisis (e.g., 2008), the weights of the good and bad factors decrease, which indicates that all the industrial portfolios (sectors) are affected. This allows us to identify the sectors most sensitive to good and bad news at different times of the economic cycle. For example, the sectors with the highest weights for the good and bad factors in the recent COVID-19 crisis were fun and hardware (for 2020), respectively. In contrast, in 2016, the medical equipment and drugs sectors show the highest weights in the good and bad factors, respectively.

Fig. 2 presents a comparison of the GUB factors and the two main factors (Mkt-Rf and SMB) of the M7 model and includes the annual mean values of the usual and Mkt-Rf factors. For the monthly returns, note that the GUB factors offer a similar (mean) return per unit of risk (standard deviation) very close to the market portfolio factor (Mkt-Rf); in contrast, the SMB factor shows a return per unit of risk that is one-third of the GUB factors.

Finally, we analyze the covariance matrix of the daily excess returns of the industrial portfolios, M7 factors, and GUB factors to check for possible multicollinearity problems. For this purpose, we estimate the eigenvalues, using principal component analysis (PCA). Table 6 shows the mean accumulated explanatory power of the rolling PCA from the covariance matrix estimates, with 1250 daily data items each.

Note that the original daily returns need 30 eigenvalues (independent factors) to explain 95% of the covariance matrix, and the M7 factors' covariance needs five eigenvalues. This result indicates multicollinearity among these seven factors. Otherwise, the covariance matrix for positive and negative outliers and usual returns of the 49 industrial portfolios need only one eigenvalue to reach 99%. Unlike the M7 factors, the GUB factor covariance matrix needs three eigenvalues (as many as the number of factors) to exceed 95%, which shows that, as opposed to the M7 factors, the GUB factors are linearly independent. Consequently, the GUB factors avoid statistical

[3] We appreciate the comment of one of the reviewers regarding the sample justification and the power of the empirical results.

[4] Note that the weights are estimated according to $A_{1,t} = w_{A,t} \cdot Z_{1,t}^{1,N}$, but we check other types of weights (equal weights, optimal mean–variance of outlier values, moving average, optimal lags, etc.), and the results indicate that the relative frequency for the estimated sample performs the best.

Table 1
Statistical summary of portfolios' daily data.

Portfolios	Obs.	Min.	Mean	Max.	Std. dev.	Skew.	E. kurt.	JB	LM	Q(2) raw	Q(2) sq.
Agric	12865	− 0.118	0.000	0.157	0.014	0.428	6.868	2567.5(**)	404.46(**)	31.70(**)	896.29(**)
Food	12865	− 0.112	0.001	0.091	0.008	− 0.359	13.764	1018.20(**)	1454.30(**)	50.96(**)	3125.73(**)
Soda	12865	− 0.127	0.001	0.165	0.014	0.326	8.225	3648.80(**)	462.62(**)	27.97(**)	1024.12(**)
Beer	12865	− 0.108	0.001	0.151	0.011	0.605	11.221	6827.50(**)	289.98(**)	8.31(*)	647.21(**)
Smoke	12865	− 0.143	0.001	0.278	0.015	1.485	29.510	47136.01(**)	60.40(**)	43.900	128.65(**)
Toys	12865	− 0.122	0.001	0.150	0.012	0.071	8.745	410.08(**)	920.04(**)	173.99(**)	2006.78(**)
Fun	12865	− 0.194	0.001	0.148	0.013	− 0.365	20.363	2225.50(**)	2281.21(**)	259.94(**)	4523.69(**)
Books	12865	− 0.146	0.000	0.179	0.012	0.286	18.045	17473.01(**)	790.29(**)	61.68(**)	1739.08(**)
Hshld	12865	− 0.124	0.000	0.136	0.010	− 0.290	14.229	1087.20(**)	1348.10(**)	276.89(**)	2869.33(**)
Clths	12865	− 0.154	0.001	0.164	0.012	0.104	17.782	1695.10(**)	1092.50(**)	245.57(**)	2359.89(**)
Hlth	12865	− 0.160	0.001	0.322	0.013	0.878	38.690	80407.01(**)	201.00(**)	285.91(**)	428.94(**)
MedEq	12865	− 0.110	0.001	0.088	0.011	− 0.558	8.014	3509.50(**)	1256.40(**)	583.17(**)	2727.55(**)
Drugs	12865	− 0.149	0.001	0.123	0.013	− 0.433	8.731	4126.51(**)	1544.50(**)	494.25(**)	3247.55(**)
Chems	12865	− 0.125	0.001	0.138	0.012	− 0.448	13.108	9253.81(**)	1251.20(**)	129.47(**)	2745.09(**)
Rubbr	12865	− 0.124	0.001	0.336	0.012	1.869	60.500	196960.01(**)	32.27(**)	67.51(**)	67.45(**)
Txtls	12865	− 0.148	0.000	0.127	0.013	− 0.212	12.172	795.16(**)	945.17(**)	168.55(**)	1955.14(**)
BldMt	12865	− 0.131	0.001	0.133	0.011	− 0.432	14.356	11088.01(**)	1928.30(**)	195.06(**)	3750.92(**)
Cnstr	12865	− 0.182	0.001	0.404	0.015	1.548	55.651	16653.10(**)	200.81(**)	175.16(**)	414.56(**)
Steel	12865	− 0.142	0.000	0.161	0.014	− 0.272	13.124	9248.10(**)	1556.30(**)	125.74(**)	3157.90(**)
FabPr	12865	− 0.153	0.000	0.153	0.015	0.134	10.682	6120.11(**)	1121.10(**)	23.37(**)	2393.16(**)
Mach	12865	− 0.126	0.001	0.115	0.012	− 0.497	13.459	9762.62(**)	1913.20(**)	153.21(**)	3772.34(**)
ElcEq	12865	− 0.134	0.001	0.123	0.012	− 0.304	8.935	4298.74(**)	1336.33(**)	233.17(**)	2713.54(**)
Autos	12865	− 0.135	0.000	0.111	0.013	− 0.179	12.196	7979.60(**)	1646.70(**)	269.14(**)	3337.58(**)
Aero	12865	− 0.148	0.001	0.158	0.013	0.032	12.278	808.06(**)	1238.4(**)	79.87(**)	2.566.20(**)
Ships	12865	− 0.132	0.000	0.125	0.017	0.054	51.960	144.79(**)	891.41(**)	9.95(**)	1.961.60(**)
Guns	12865	− 0.171	0.001	0.221	0.015	0.958	14.535	11521(**)	256.39(**)	6.25(*)	554.36(**)
Gold	12865	− 0.182	0.001	0.247	0.024	0.444	57.862	183.7(**)	459.44(**)	15.85(**)	1030.55(**)
Mines	12865	− 0.148	0.001	0.145	0.017	0.118	66.786	239.4(**)	798.96(**)	38.68(**)	1763.20(**)
Coal	12865	− 0.258	0.000	0.423	0.025	0.581	15.098	12291(**)	744.71(**)	13.700	1664.68(**)
Oil	12865	− 0.282	0.001	0.252	0.017	0.074	24.369	318350(**)	971.96(**)	153.16(**)	2202.45(**)
Util	12865	− 0.117	0.000	0.133	0.008	− 0.016	31.442	52995(**)	2538.70(**)	49.09(**)	5023.71(**)
Telcm	12865	− 0.117	0.001	0.131	0.013	− 0.162	94.279	477.02(**)	2123.61(**)	263.21(**)	4246.04(**)
PerSv	12865	− 0.148	0.001	0.107	0.012	− 0.223	10.411	582.04(**)	1730.82(**)	119.60(**)	3678.28(**)
BusSv	12865	− 0.134	0.001	0.107	0.011	− 0.688	12.740	880.12(**)	2050.13(**)	391.22(**)	3941.66(**)
Hardw	12865	− 0.140	0.001	0.136	0.014	− 0.213	79.157	336.84(**)	1310.10(**)	399.93(**)	2732.50(**)
Softw	12865	− 0.208	0.001	0.242	0.019	0.304	17.892	17179(**)	609.43(**)	57.93(**)	1375.20(**)
Chips	12865	− 0.122	0.001	0.122	0.013	− 0.190	76.337	313.14(**)	1351.75(**)	487.22(**)	2844.17(**)
LabEq	12865	− 0.113	0.001	0.119	0.012	− 0.290	78.116	328.9(**)	1166.64(**)	424.39(**)	2495.85(**)
Paper	12865	− 0.133	0.000	0.149	0.012	− 0.045	18.230	17814(**)	1246.70(**)	95.53(**)	2738.61(**)
Boxes	12865	− 0.116	0.000	0.163	0.013	0.025	94.835	482.11(**)	959.93(**)	6.71(*)	2124.64(**)
Trans	12865	− 0.131	0.000	0.118	0.012	− 0.411	10.562	601.59(**)	1301.60(**)	186.28(**)	2777.98(**)
Whlsl	12865	− 0.114	0.001	0.094	0.010	− 0.526	12.886	896.04(**)	1886.82(**)	348.59(**)	3805.12(**)
Rtail	12865	− 0.129	0.000	0.123	0.011	− 0.272	13.843	10289(**)	1541.10(**)	257.18(**)	3198.21(**)
Meals	12865	− 0.191	0.001	0.168	0.011	− 0.261	22.440	270080(**)	1582.11(**)	322.35(**)	3187.01(**)
Banks	12865	− 0.131	0.001	0.094	0.009	− 0.356	24.854	33141(**)	2937.70(**)	218.62(**)	5844.85(**)
Insur	12865	− 0.126	0.001	0.146	0.010	− 0.241	23.025	28430(**)	2588.52(**)	56.34(**)	4827.27(**)
RlEst	12865	− 0.155	0.001	0.223	0.014	0.462	17.750	16935(**)	1995.83(**)	41.51(**)	4064.09(**)
Fin	12865	− 0.135	0.001	0.109	0.010	− 0.272	17.631	16679(**)	2549.80(**)	68.66(**)	4882.83(**)
Other	12865	− 0.136	0.001	0.122	0.012	− 0.105	13.264	943.26(**)	1146.01(**)	108.57(**)	2482.26(**)

Note: The term JB stands for the Jarque–Bera test of data normality, and the null hypothesis is Gaussian behavior; LM is an autoregressive conditional heteroskedasticity (ARCH) test that shows the heteroscedasticity (lag 2) of the data, and the null hypothesis is the absence of heteroscedasticity; Q(2) raw and Q(2) sq. stand for the Box–Pierce test measuring the autoregression on the data and squared data, the null being that these characteristics do not exist. (**) and (*) indicate that the null hypothesis is rejected at the 1% and 5% confidence levels, respectively.

Table 2
Statistical summary of portfolios' monthly data.

Portfolios	Obs.	Min.	Mean	Max.	Std. dev.	Skew.	E. kurt.	JB	LM	Q(2) raw	Q(2) sq.
Agric	612	− 0.312	0.003	0.515	0.074	0.789	5.601	863.51(**)	0.39	14.17(**)	0.79
Food	612	− 0.261	0.007	0.203	0.045	− 0.548	3.556	353.02(**)	3.44(*)	16.10(**)	7.43(*)
Soda	612	− 0.236	0.010	0.510	0.070	0.893	6.175	1053.40(**)	0.35	1.59	0.71
Beer	612	− 0.200	0.008	0.317	0.055	0.367	3.553	335.69(**)	1.17	3.35	2.42
Smoke	612	− 0.253	0.014	0.534	0.075	1.171	6.572	1241.10(**)	2.02	9.05(*)	4.25
Toys	612	− 0.304	0.004	0.364	0.077	0.412	3.115	264.64(**)	8.06(**)	13.55(**)	17.38(**)
Fun	612	− 0.396	0.006	0.410	0.075	0.127	4.560	531.89(**)	13.03(**)	22.71(**)	28.97(**)
Books	612	− 0.339	0.006	0.531	0.068	0.648	9.855	2519.20(**)	8.81(**)	33.95(**)	19.49(**)
Hshld	612	− 0.303	0.005	0.397	0.064	0.105	4.768	580.80(**)	11.62(**)	29.77(**)	25.83(**)
Clths	612	− 0.326	0.006	0.400	0.069	0.120	4.334	480.55(**)	5.25(**)	32.94(**)	10.65(**)
Hlth	612	− 0.390	0.009	0.377	0.079	− 0.071	3.204	262.36(**)	8.11(**)	41.46(**)	17.03(**)
MedEq	612	− 0.307	0.008	0.303	0.071	0.029	2.063	108.60(**)	2.9	25.94(**)	5.99(*)
Drugs	612	− 0.335	0.012	0.632	0.083	0.710	5.736	890.40(**)	26.50(**)	20.94(**)	59.06(**)
Chems	612	− 0.313	0.007	0.237	0.062	− 0.451	2.783	218.27(**)	13.05(**)	13.76(**)	28.91(**)
Rubbr	612	− 0.312	0.008	0.360	0.068	0.017	3.065	239.52(**)	13.21(**)	19.84(**)	29.05(**)
Txtls	612	− 0.327	0.004	0.509	0.076	0.392	5.533	796.21(**)	15.13(**)	46.17(**)	34.24(**)
BldMt	612	− 0.295	0.008	0.384	0.065	0.111	3.715	353.13(**)	1.46	17.98(**)	3.08
Cnstr	612	− 0.308	0.005	0.513	0.079	0.533	4.539	554.29(**)	1.93	21.88(**)	4.06
Steel	612	− 0.318	0.006	0.340	0.074	− 0.075	2.295	134.91(**)	5.83(**)	8.79(*)	12.59(**)
FabPr	612	− 0.282	0.004	0.440	0.073	0.075	3.090	244.08(**)	8.20(**)	17.59(**)	16.84(**)
Mach	612	− 0.322	0.008	0.239	0.066	− 0.466	2.398	168.69(**)	5.34(**)	17.82(**)	10.98(**)
ElcEq	612	− 0.310	0.007	0.325	0.071	− 0.040	1.973	99.46(**)	4.55(*)	17.68(**)	9.12(*)
Autos	612	− 0.352	0.006	0.394	0.075	− 0.001	3.873	382.57(**)	13.43(**)	21.44(**)	29.57(**)
Aero	612	− 0.320	0.010	0.363	0.072	0.057	3.336	284.19(**)	3.12(*)	11.59(**)	6.73(*)
Ships	612	− 0.437	0.007	0.400	0.081	0.024	3.738	356.40(**)	2.27	6.00(*)	4.78
Guns	612	− 0.296	0.012	0.272	0.072	0.243	1.245	45.56(**)	0.38	13.16(**)	0.73
Gold	612	− 0.433	0.007	0.569	0.122	0.874	2.362	220.19(**)	6.61(**)	2.29()	14.12(**)
Mines	612	− 0.353	0.006	0.376	0.085	0.258	2.211	131.40(**)	11.65(**)	20.34(**)	24.83(**)
Coal	612	− 0.402	0.002	0.800	0.115	0.753	5.062	711.19(**)	25.34(**)	3.23	58.33(**)
Oil	612	− 0.494	0.005	0.720	0.092	0.443	7.493	1451.70(**)	44.62(**)	4.58	79.58(**)
Util	612	− 0.131	0.007	0.222	0.036	− 0.016	2.494	158.60(**)	1.42	5.08	2.89
Telcm	612	− 0.279	0.008	0.526	0.075	0.349	5.135	684.82(**)	20.87(**)	25.97(**)	43.51(**)
PerSv	612	− 0.313	0.005	0.268	0.067	− 0.175	2.179	124.22(**)	4.52(*)	14.73(**)	9.67(**)
BusSv	612	− 0.312	0.008	0.328	0.068	− 0.228	2.852	212.76(**)	4.58(*)	28.92(**)	9.87(**)
Hardw	612	− 0.339	0.008	0.488	0.091	0.465	2.808	223.14(**)	17.56(**)	18.07(**)	39.83(**)
Softw	612	− 0.523	0.006	0.731	0.108	0.436	6.205	1001.10(**)	53.04(**)	3.68	105.39(**)
Chips	612	− 0.335	0.010	0.448	0.088	0.286	2.499	167.54(**)	14.07(**)	18.94(**)	31.03(**)
LabEq	612	− 0.309	0.010	0.368	0.074	0.077	1.896	92.29(**)	9.08(**)	30.83(**)	20.22(**)
Paper	612	− 0.281	0.006	0.350	0.061	− 0.134	4.168	444.87(**)	44.86(**)	22.74(**)	94.27(**)
Boxes	612	− 0.280	0.007	0.239	0.064	− 0.253	1.961	104.61(**)	4.51(*)	7.91(*)	9.82(**)
Trans	612	− 0.304	0.006	0.248	0.064	− 0.262	2.188	129.10(**)	2.97	16.96(**)	6.30(*)
Whlsl	612	− 0.298	0.006	0.324	0.064	− 0.050	2.928	218.88(**)	5.42(**)	30.78(**)	11.63(**)
Rtail	612	− 0.320	0.006	0.364	0.068	0.208	4.053	423.31(**)	11.12(**)	32.58(**)	23.29(**)
Meals	612	− 0.396	0.005	0.359	0.068	− 0.112	5.959	906.83(**)	23.37(**)	26.16(**)	44.18(**)
Banks	612	− 0.257	0.007	0.289	0.051	− 0.235	3.787	371.29(**)	4.02(*)	32.07(**)	8.42(*)
Insur	612	− 0.231	0.008	0.201	0.049	− 0.617	2.503	198.66(**)	15.59(**)	23.53(**)	34.46(**)
RlEst	612	− 0.331	0.003	0.527	0.075	0.535	6.400	1073.80(**)	6.82(**)	23.45(**)	15.15(**)
Fin	612	− 0.226	0.007	0.266	0.054	− 0.188	2.445	156.01(**)	9.14(**)	24.56(**)	19.32(**)
Other	612	− 0.332	0.004	0.383	0.070	− 0.060	3.543	320.40(**)	5.99(**)	30.31(**)	12.56(**)

Note: The term JB stands for the Jarque–Bera test of data normality, and the null hypothesis is Gaussian behavior; LM is an autoregressive conditional heteroskedasticity (ARCH) test that shows the heteroscedasticity (lag 2) of the data, and the null hypothesis is the absence of heteroscedasticity; Q(2) raw and Q(2) sq. stand for the Box–Pierce test measuring the autoregression on the data and squared data, the null being that these characteristics do not exist. (**) and (*) indicate that the null hypothesis is rejected at the 1% and 5% confidence levels, respectively.

Table 3
Summary statistics of the factor data.

Factors	Obs.	Min.	Mean	Max.	Std. dev.	Skew.	E. kurt.	JB	LM	Q(2) raw	Q(2) sq.
	Daily data										
Mkt-Rf	12,865	− 0.1744	0.0003	0.1135	0.0105	− 0.5478	159.030	1362.10(**)	1129.81(**)	29.931	2295.44(**)
SMB	12,865	− 0.1117	0.0003	0.0608	0.0055	− 0.8011	198.510	2126.11(**)	589.77(**)	17.54(**)	1105.12(**)
HML	12,865	− 0.0472	0.0001	0.0483	0.0055	0.2682	106.720	612.01(**)	1335.61(**)	206.23(**)	3005.28(**)
RMW	12,865	− 0.0292	0.0001	0.0440	0.0038	0.3396	95.493	491.28(**)	1226.20(**)	271.32(**)	2717.99(**)
CMA	12,865	− 0.0594	0.0001	0.0253	0.0037	− 0.4013	111.600	671.02(**)	494.87(**)	249.55(**)	1068.11(**)
WML	12,865	− 0.0821	0.0003	0.0701	0.0075	− 0.9657	138.300	1045.30(**)	1020.90(**)	546.71(**)	2303.33(**)
QMJ	12,865	− 0.0374	0.0002	0.0503	0.0042	0.16379	110.720	657.69(**)	810.65(**)	152.84(**)	1847.23(**)
	Monthly data										
Mkt-Rf	612	− 0.2324	0.0054	0.1610	0.0457	− 0.5410	18.274	115.01(**)	6.99(**)	31.043	15.22(**)
SMB	612	− 0.1491	0.0014	0.1832	0.0302	0.3864	34.989	28.11(**)	28.11(**)	14.141	57.28(**)
HML	612	− 0.1412	0.0024	0.1287	0.0298	− 0.0626	23.061	136.01(**)	33.98(**)	22.97(**)	75.60(**)
RMW	612	− 0.1834	0.0029	0.1333	0.0221	− 0.3420	124.080	393.76(**)	76.56(**)	18.44(**)	164.66(**)
CMA	612	− 0.0686	0.0029	0.0956	0.0199	0.3483	15.917	76.98(**)	73.03(**)	11.66(**)	161.50(**)
WML	612	− 0.3439	0.0064	0.1836	0.0434	− 12.719	97.719	260.01(**)	16.69(**)	22.700	36.40(**)
QMJ	612	− 0.0910	0.0041	0.1241	0.0233	0.2150	25.815	174.64(**)	35.24(**)	17.75(**)	79.33(**)

Note: The term JB stands for the Jarque–Bera test of data normality, and the null hypothesis is Gaussian behavior; LM is an autoregressive conditional heteroskedasticity (ARCH) test that shows the heteroscedasticity (lag 2) of the data, and the null hypothesis is the absence of heteroscedasticity; Q(2) raw and Q(2) sq. stand for the Box–Pierce test measuring the autoregression on the data and squared data, the null being that these characteristics do not exist. (**) and (*) indicate that the null hypothesis is rejected at the 1% and 5% confidence levels, respectively.

Table 4
Correlation matrix of the asset pricing factors.

Factor	Mkt-Rf	SMB	HML	RMW	CMA	WML	QMJ
	Daily data						
Mkt-Rf	1						
SMB	0.4291	1					
HML	− 0.6090	− 0.3146	1				
RMW	− 0.1040	− 0.2050	− 0.3677	1			
CMA	− 0.6337	− 0.3856	0.8645	− 0.2160	1		
WML	− 0.4413	− 0.4166	0.2976	0.2446	0.4045	1	
QMJ	− 0.7175	− 0.5130	0.3338	0.4362	0.4821	0.5436	1
	Monthly data						
Mkt-Rf	1						
SMB	0.2745	1					
HML	− 0.2288	− 0.0450	1				
RMW	− 0.2290	− 0.3580	0.1065	1			
CMA	− 0.3881	− 0.0811	0.6888	0.0219	1		
WML	− 0.1734	− 0.0825	− 0.2039	0.0996	0.0046	1	
QMJ	− 0.5246	− 0.4742	− 0.0487	0.7240	0.0824	0.3026	1

problems when estimating expressions (1) and (2).

4.2. Anomaly results

One of the most relevant pieces of empirical evidence of this study is presented in Table 7. This tables shows the percentages of anomalies for each industrial portfolio and both daily and monthly frequencies and both models (expressions (1) and (2)). For each portfolio, the results represent the number of estimates[5] in which α (a constant) is significant at the 5% and 1% confidence levels with respect to the total estimates (11,616 for the daily frequency and 553 for the monthly frequency).

Note that, when going from a 5% to a 1% confidence level, the number of anomalies decreases substantially for all portfolios and frequencies. We observe an enormous drop in the number of anomalies for the GUB model with respect to the M7 model for both confidence levels and both frequencies. For example, at the 5% level, the agriculture (daily) and wholesale (monthly) portfolios show

[5] The results are obtained by OLS. The same analysis was also carried out with the results using FGLS, and the results are very similar. The latter are not tabulated, but are available from the author upon request.

Table 5
Average weights of industrial portfolios.

Portfolio	Daily			Monthly		
	G	U	B	G	U	B
Agric	1.64%	2.08%	1.48%	3.88%	2.03%	1.86%
Food	0.98%	2.10%	1.29%	0.97%	2.04%	3.48%
Soda	1.65%	2.07%	1.47%	3.77%	2.04%	2.33%
Beer	1.08%	2.11%	0.88%	2.89%	2.03%	5.41%
Smoke	1.74%	2.08%	1.52%	5.20%	2.03%	3.63%
Toys	0.90%	2.12%	0.79%	2.76%	2.04%	1.11%
Fun	1.16%	2.10%	1.25%	2.12%	2.04%	2.36%
Books	1.23%	2.09%	1.22%	1.68%	2.04%	2.17%
Hshld	1.66%	2.05%	1.80%	0.91%	2.04%	2.64%
Clths	1.14%	2.10%	1.28%	1.63%	2.04%	1.95%
Hlth	1.55%	2.07%	1.54%	1.57%	2.05%	2.48%
MedEq	3.64%	1.94%	3.78%	1.54%	2.04%	0.98%
Drugs	3.55%	1.94%	3.92%	2.10%	2.04%	3.39%
Chems	1.51%	2.06%	1.80%	0.96%	2.04%	3.70%
Rubbr	1.62%	2.08%	1.38%	1.03%	2.04%	1.70%
Txtls	1.95%	2.06%	1.94%	2.67%	2.03%	1.69%
BldMt	2.23%	2.01%	2.23%	0.80%	2.05%	1.11%
Cnstr	1.43%	2.10%	1.26%	2.46%	2.04%	0.89%
Steel	1.60%	2.07%	1.57%	2.14%	2.04%	1.61%
FabPr	1.05%	2.12%	0.86%	1.82%	2.03%	1.61%
Mach	2.75%	1.97%	2.94%	0.26%	2.05%	0.93%
ElcEq	1.98%	2.03%	2.19%	0.36%	2.05%	0.84%
Autos	1.76%	2.05%	1.96%	1.31%	2.03%	2.76%
Aero	1.26%	2.09%	1.23%	3.97%	2.04%	2.64%
Ships	1.57%	2.08%	1.50%	2.16%	2.05%	0.70%
Guns	1.84%	2.07%	1.60%	1.16%	2.06%	1.53%
Gold	2.19%	2.06%	1.36%	9.48%	2.03%	0.29%
Mines	1.51%	2.09%	1.15%	4.81%	2.04%	0.64%
Coal	1.85%	2.07%	1.58%	3.47%	2.05%	0.51%
Oil	2.41%	2.03%	2.28%	1.98%	2.05%	0.87%
Util	2.12%	2.02%	2.63%	0.91%	2.05%	2.58%
Telcm	1.56%	2.05%	1.98%	1.73%	2.05%	0.94%
PerSv	1.22%	2.10%	1.11%	0.68%	2.05%	0.80%
BusSv	4.02%	1.89%	4.06%	0.76%	2.05%	0.93%
Hardw	2.71%	1.97%	3.10%	2.04%	2.04%	1.36%
Softw	3.98%	1.92%	4.37%	1.81%	2.05%	0.95%
Chips	3.84%	1.92%	3.99%	1.18%	2.05%	0.77%
LabEq	2.01%	2.03%	2.07%	1.29%	2.05%	0.71%
Paper	1.07%	2.10%	1.22%	1.49%	2.04%	1.80%
Boxes	1.18%	2.10%	1.13%	1.67%	2.04%	6.36%
Trans	1.33%	2.09%	1.37%	1.36%	2.04%	4.81%
Whlsl	3.82%	1.92%	3.83%	1.19%	2.04%	1.24%
Rtail	2.39%	2.00%	2.62%	2.31%	2.03%	1.28%
Meals	1.64%	2.06%	1.92%	1.46%	2.03%	3.06%
Banks	2.74%	1.99%	2.54%	1.40%	2.03%	1.98%
Insur	2.76%	1.97%	2.88%	0.29%	2.04%	2.29%
RlEst	1.90%	2.06%	1.59%	3.74%	2.02%	1.70%
Fin	4.94%	1.87%	4.18%	1.48%	2.03%	2.17%
Other	2.35%	2.02%	2.35%	1.35%	2.05%	0.86%

more than 80% fewer anomalies, whereas, at the 1% level, more portfolios show such a large difference: namely, building materials, boxes, chemicals, fabricated products, household products, toys, and transportation (daily) and automobiles, building materials, paper, and rubber (monthly).

For the 5% confidence level and daily frequency, the highest decrease in anomalies is 85% (fabricated products, daily), the average is 46%, and the lowest decrease is − 10% (oil, daily). If the confidence level is 1%, then the highest decrease is 90% (building materials, daily), the average is 54%, and the minimum is 2.17% (oil, daily). For the monthly frequency and at the 5% level of confidence, the maximum is 86% (rubber, monthly), the average is 50%, and the minimum is 5% (beer, monthly). Finally, at the 1% level, the maximum decrease is 90% (rubber, monthly), the average decrease is 60%, and the smallest decrease is 29% (utilities, monthly).

In short, regarding the horse race of the anomalies between the magnificent seven model and the GUB model, the latter is clearly the winner, since, at a confidence level of 5%, the average decrease in the anomalies of the GUB factors model with respect to the M7 factors model is between 46% and 50% for the daily and monthly frequencies, respectively. This difference increases at the 1% confidence level, showing values between 54% and 60% for the daily and monthly frequencies, respectively.

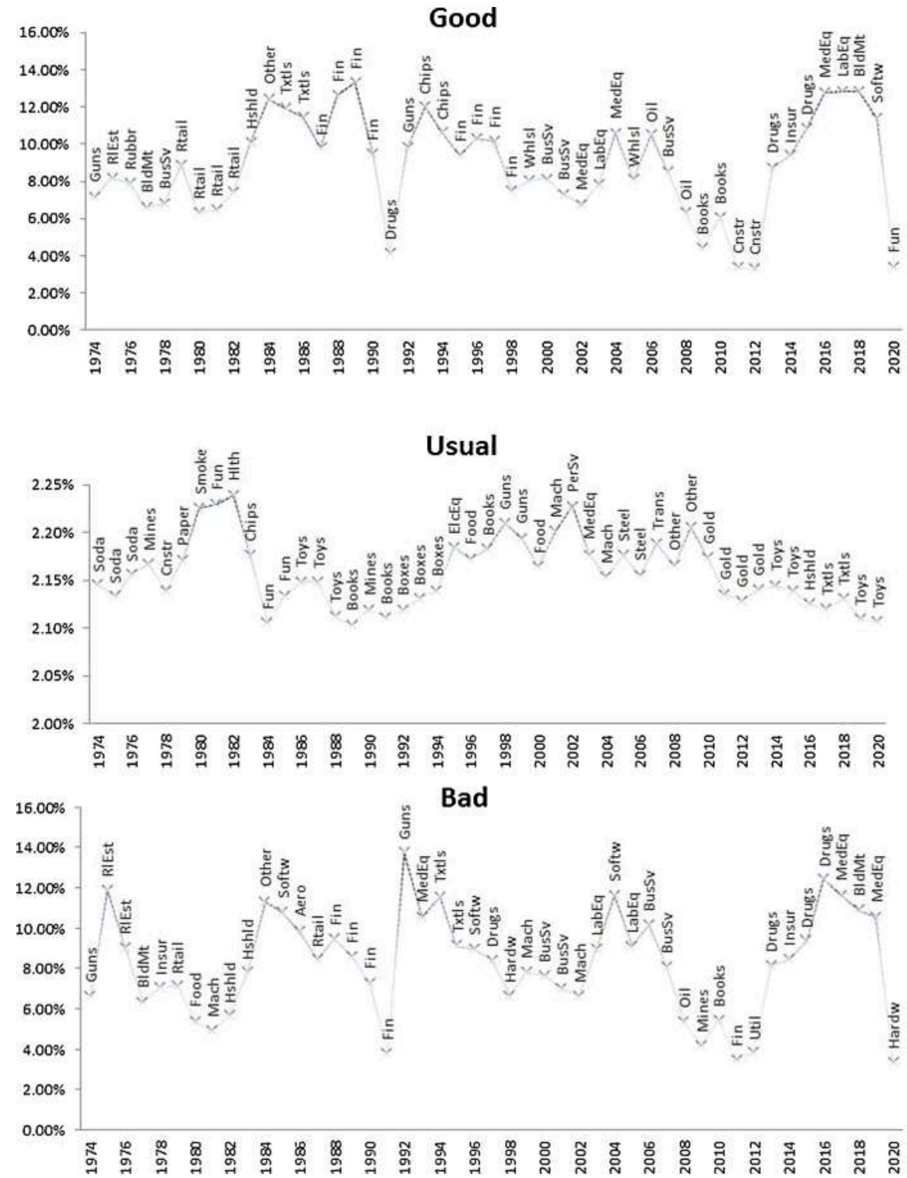

Fig. 1. Industrial portfolios with the highest annual average weights.

4.3. Robustness analysis

To analyze the validity of the previous results, we compare the robustness of both the M7 and the GUB models by estimating the tests proposed in the methodological section. Table 8 shows the results for each industrial portfolio for the mean α values, the alpha ratio, the mean adjusted R^2 values, and the mean R^2_{out} values. Table 9 presents the results of the GRS tests.

The first column in Table 8 shows the performance of each model measured by $\frac{\text{average}(\alpha_i^2)}{\text{average}(r_i^2)}$, and the lower the value, the higher the performance (the lower the intercept dispersion to the total dispersion). Note that the GUB model presents lower values than the M7 model, except for six industrial portfolios with a daily frequency (soda, beer, smoke or tobacco, oil, coal, and utilities) and 14 with a monthly frequency (soda, beer, smoke, oil, coal, utilities, hardware, software, paper, boxes, retail, banks, insurance, and finance).

The second column in Table 8 shows the proportion of unexplained dispersion attributable to sampling error measured by $\frac{\text{average}[s^2(\alpha_i)]}{\text{average}(\alpha_i^2)}$, and the higher the value, the higher the performance (the dispersion of the intercepts is mainly due to sampling error). Note that only for two industrial portfolios and a monthly frequency (medical equipment and drugs) does the GUB model presents lower values than the M7 model, and the GUB model shows lower sampling errors than the M7 model.

The third column in Table 8 shows the mean R^2. Only 13 (of a total of 49) industrial portfolios for the daily frequency and 17

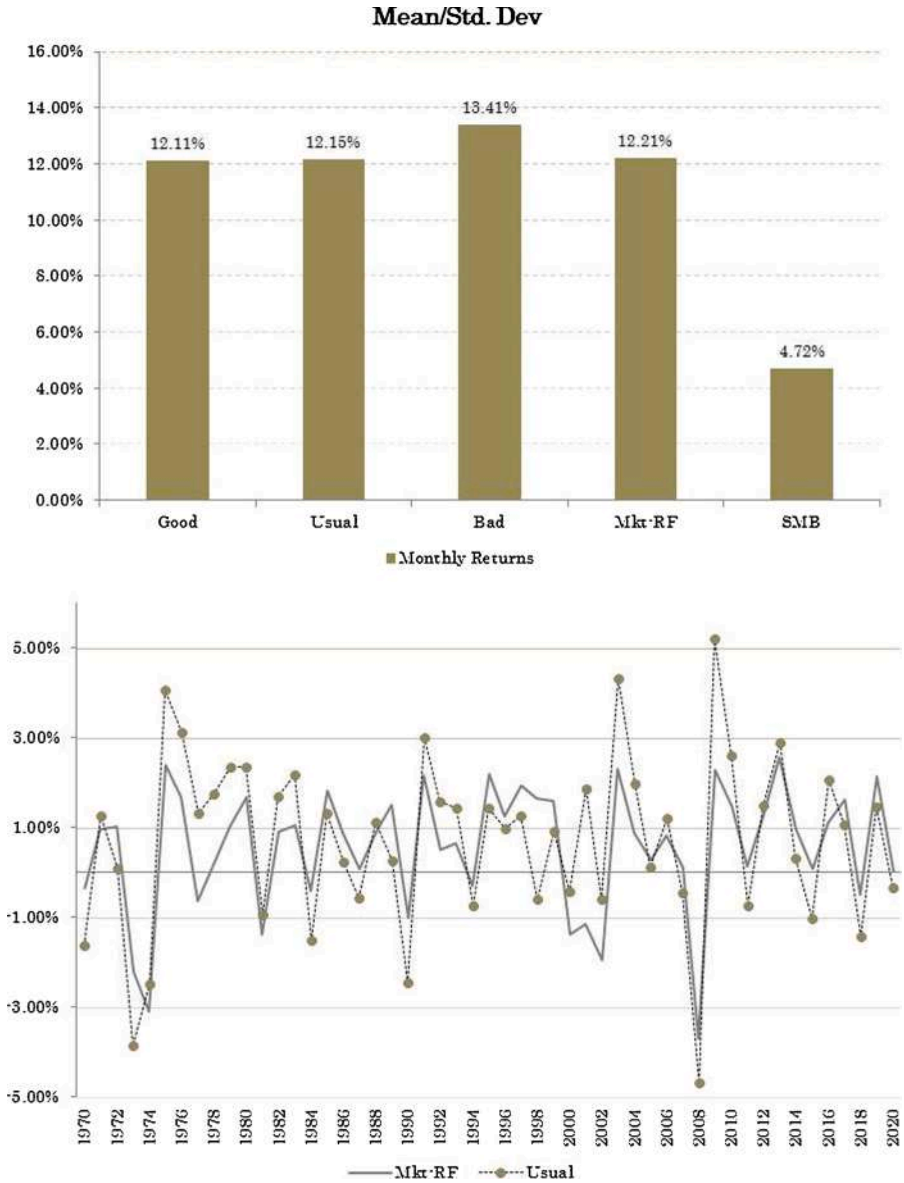

Fig. 2. GUB factors versus the Mkt-Rf and SMB factors.

industrial portfolios for the monthly frequency show that the M7 model have a mean explanatory power higher than the GUB model's. In particular, for the daily frequency, these industrial portfolios are soda, beer, smoke, drugs, mines, coal, oil, utilities, hardware, chips, retail, banks, and insurance. For the monthly frequency, telecommunications, software, paper, boxes, and finance are added to the above in daily frequency, while mines disappears.

The last column in Table 8 shows the results of R^2_{out}. In all cases, the values are negative, so we accept the unpredictability hypothesis, or efficient markets. We also observe for the monthly frequency higher values than for the daily frequency, and higher absolute values for the M7 model than for the GUB model. From this, we deduce that the daily prediction of the proposed models is worse at the daily frequency than at the monthly frequency, and worse for the M7 factors model than for the GUB factors model.

Table 9 summarizes the GRS test results, with the minimum, median, and maximum test values for each model estimated by OLS and FGLS.

Table 9 shows that, for the M7 model and daily frequency, the hypothesis of the joint null of all the alphas for the industrial portfolios is not accepted in any of the cases, although, for the monthly frequency, the probability is slightly higher than for the daily frequency. On the other hand, for the GUB model at the daily frequency, the joint hypothesis is accepted at 1% at confidence level from the median (50% of the cases) in the OLS estimate, whereas, for the FGLS estimate, it is accepted for 100% of the cases and that level of confidence. At the monthly frequency, for the GUB model, the hypothesis is only accepted from the median for both estimate methods.

Table 6
Accumulated explanatory power of eigenvalues.

Eigenvalue	Original daily data	M7 daily factors	Good daily data	Usual daily data	Bad daily data	GUB daily factors
1	50.98%	55.71%	99.03%	99.04%	99.05%	58.43%
2	60.41%	74.72%	99.10%	99.07%	99.08%	81.82%
3	65.87%	85.66%				100.00%
4	69.49%	92.50%				
5	72.51%	95.03%				
6	74.99%					
7	77.05%					
8	78.84%					
9	80.41%					
10	81.82%					
11	83.11%					
12	84.28%					
13	85.38%					
14	86.40%					
15	87.35%					
16	88.22%					
17	89.03%					
18	89.77%					
19	90.45%					
20	91.08%					
21	91.67%					
22	92.22%					
23	92.70%					
24	93.10%					
25	93.51%					
26	93.89%					
27	94.23%					
28	94.54%					
29	94.83%					
30	95.10%					

This result indicates that, as the time series decreases its frequency of observations and becomes more Gaussian, the GUB model has fewer statistical advantages. Therefore, the GUB factors model is more consistent than the M7 factors model when analyzing high-frequency data. This result is relevant to investors and investment managers who trade assets or make decisions at frequencies of less than one month.

4.4. Analysis of betas

To analyze the sensitivity (β) of each industrial portfolio to the different factors, we estimate the average betas. Table 10 shows the average of statistically significant betas for all factors and models at the daily frequency. These average betas are estimated as the arithmetic mean of the rolling betas estimated when they are statistically significant at least at 5% for the total 11,616 regressions performed for each industry portfolio.

Note that the percentages of significant cases for the three factors of the GUB model are 60–100%, while, for the M7 model, the percentages vary for each factor as follows: Mkt-Rf, 69–100%; SMB, 69–100%; HML, 22–100%; RMW, 13–92%; CMA, 18–83%; WML, 24–93%; and QMJ, 20–96%. Therefore, only Mkt-Rf and SMB show a significant percentage similar to the GUB factors. Besides, the variability of the M7 beta values is greater than for the GUB betas. In addition, the latter are all positive. For each factor, the average β values have the following ranges: good (0.448–1.346), bad (0.434–1.222), usual (0.531–1.196), Mkt-Rf (0.416–1.044), SMB (0.203–0.898), HML ($-$ 1.032–0.388), RMW ($-$ 0.491–0.561), CMA ($-$ 0.558–0.467), WML ($-$ 0.191–0.111), and QMJ ($-$ 1.432–0.460).

For the monthly frequency, Table 11 shows the average of the significant β values (for each factor of both models) calculated from the 553 rolling regressions estimated for each industry portfolio, and, as in the case of daily frequency, whether the β for each factor is significant at least at the 5% confidence level.

The monthly frequency results of Table 11 show that the percentages of significant cases for all the factors decrease, but the GUB factors display higher values, as follows: good, 23–100%; bad, 30–100%; usual, 19–100%; Mkt-Rf, 18–100%; SMB, 10–100%; HML, 3–88%; RMW, 3–49%; CMA, 3–46%; WML, 10–64%; and QMJ, 6–74%. The average of the monthly significant betas for the M7 model show important changes with respect to the daily values that we can hardly justify for the RMW, CMA, WML, and QMJ factors. On the other hand, for the GUB model, only the good and bad factors show important changes with respect to the daily average betas. These results are justified, because the monthly data show fewer outliers, since their behavior is more Gaussian than for the daily frequency.

Although we use HAC standard errors to measure the statistical significance of the betas analyzed above, we perform a statistical analysis of the residuals of the estimated models (expressions (1) and (2)) to check the robustness of the previous results. Table 12 shows the maximum–minimum range of values for the autoregression tests using raw and squared data (residuals) and heteroscedasticity. The results indicate that these tests on the residuals of both models for the monthly frequency do not reject the null

Table 7
Percentages of anomalies.

Portfolios	At the 5% confidence level				At the 1% confidence level			
	M7 daily	GUB daily	M7 monthly	GUB monthly	M7 daily	GUB daily	M7 monthly	GUB monthly
Agric	98.65%	18.23%	61.12%	22.06%	84.17%	6.98%	54.43%	6.69%
Food	82.95%	65.58%	86.26%	49.73%	74.48%	49.34%	83.18%	23.87%
Soda	62.99%	34.82%	73.60%	24.59%	49.91%	19.52%	70.34%	11.39%
Beer	75.78%	46.87%	69.08%	64.20%	65.58%	31.38%	64.38%	33.45%
Smoke	66.57%	27.01%	77.58%	27.31%	60.28%	17.23%	75.77%	2.71%
Toys	96.68%	33.53%	83.00%	38.52%	91.28%	9.81%	78.66%	12.84%
Fun	83.11%	56.62%	74.32%	24.95%	60.59%	32.70%	65.64%	9.22%
Books	88.87%	47.94%	71.25%	40.69%	81.40%	34.15%	63.11%	21.34%
Hshld	99.99%	22.84%	92.59%	18.44%	87.67%	2.76%	84.63%	7.23%
Clths	97.33%	34.79%	87.34%	18.99%	91.81%	17.64%	82.82%	9.22%
Hlth	91.33%	68.15%	78.48%	26.04%	74.88%	43.51%	71.07%	5.06%
MedEq	90.61%	53.17%	82.64%	11.21%	74.23%	36.42%	73.96%	1.99%
Drugs	71.27%	40.47%	79.39%	12.84%	62.63%	20.62%	72.51%	1.63%
Chems	97.24%	21.87%	96.38%	33.09%	94.37%	10.78%	90.24%	17.72%
Rubbr	98.63%	41.36%	93.67%	7.59%	95.72%	17.78%	91.32%	1.63%
Txtls	93.86%	53.81%	77.94%	43.04%	86.52%	37.22%	71.97%	26.40%
BldMt	100.00%	28.72%	93.85%	14.29%	99.41%	9.32%	89.15%	0.00%
Cnstr	92.69%	24.77%	81.19%	35.99%	85.29%	7.37%	75.59%	20.61%
Steel	93.01%	56.80%	88.07%	37.25%	91.05%	41.10%	81.56%	22.24%
FabPr	93.60%	8.35%	67.63%	20.80%	83.61%	0.71%	64.01%	4.16%
Mach	96.91%	40.59%	72.15%	36.35%	90.37%	24.65%	68.17%	11.39%
ElcEq	95.16%	35.98%	87.70%	26.94%	90.19%	22.14%	78.30%	9.95%
Autos	100.00%	35.19%	93.67%	14.83%	99.85%	19.30%	90.42%	3.98%
Aero	79.59%	45.23%	71.79%	19.17%	68.67%	24.70%	66.91%	6.69%
Ships	75.95%	14.19%	62.39%	12.66%	70.65%	1.76%	57.32%	1.08%
Guns	48.21%	20.45%	41.77%	16.46%	32.19%	6.02%	39.42%	6.33%
Gold	51.76%	24.55%	46.84%	8.14%	46.89%	10.14%	43.22%	0.00%
Mines	70.05%	24.96%	69.26%	17.90%	65.70%	10.09%	64.38%	5.42%
Coal	55.75%	47.63%	61.84%	29.29%	51.92%	33.50%	57.87%	3.98%
Oil	61.74%	71.54%	56.60%	40.87%	55.99%	58.16%	47.02%	16.27%
Util	64.82%	36.18%	52.08%	45.93%	53.53%	19.59%	44.48%	15.55%
Telcm	93.72%	35.80%	79.75%	36.17%	87.54%	19.64%	76.49%	21.16%
PerSv	80.33%	31.74%	89.87%	26.94%	73.88%	17.30%	77.76%	10.85%
BusSv	97.00%	68.32%	95.66%	22.06%	90.88%	58.06%	84.09%	4.34%
Hardw	95.20%	48.69%	90.96%	33.09%	89.20%	34.91%	86.98%	19.35%
Softw	79.41%	47.14%	71.25%	28.03%	69.94%	34.00%	66.00%	15.37%
Chips	84.26%	47.00%	78.12%	31.10%	78.37%	29.72%	73.24%	17.54%
LabEq	97.34%	69.82%	80.47%	40.14%	91.37%	51.31%	68.90%	22.78%
Paper	100.00%	25.10%	99.46%	20.07%	92.00%	12.14%	92.95%	4.70%
Boxes	97.77%	21.80%	81.19%	31.28%	93.42%	12.50%	74.86%	11.03%
Trans	99.71%	24.85%	81.37%	7.41%	92.40%	9.54%	73.06%	0.00%
Whlsl	97.31%	49.46%	92.41%	11.21%	94.96%	23.29%	88.25%	1.99%
Rtail	96.67%	40.21%	87.70%	22.42%	93.84%	21.75%	84.27%	8.50%
Meals	94.46%	30.70%	81.74%	21.34%	89.19%	19.61%	78.12%	8.86%
Banks	94.39%	73.74%	79.75%	58.41%	80.41%	60.98%	72.69%	42.13%
Insur	90.32%	55.95%	72.51%	52.08%	79.80%	38.88%	66.37%	34.18%
RlEst	96.27%	53.43%	93.13%	45.21%	92.48%	23.58%	88.61%	26.40%
Fin	99.45%	65.56%	86.98%	42.68%	93.30%	54.53%	81.92%	26.04%
Other	83.17%	40.36%	74.50%	24.95%	70.33%	19.78%	64.38%	16.64%

hypothesis. However, for the daily frequency, as usual, the null hypothesis is rejected for the M7 model in all cases, while the GUB model accepts the null for any case. This is a consequence of how the GUB factors are constructed.

4.5. Comparison at one point

Although, for the whole sample period studied, the GUB factor model performs better than the M7 factor model in explaining the excess returns of the industrial portfolios, we also compare the M7 and GUB models for a specific date, or comparison at one point. To do so, we select the dates, for both monthly and daily frequencies, when the M7 model has the three best and three worst levels of explanatory power (adj. R^2). Table 13 shows the results.

Table 13 and the three dates with the worst explanatory power for both the monthly and daily frequencies show that the GUB model presents greater explanatory power than the M7 model. In contrast, for the three dates with the best explanatory powers, the GUB model has a higher daily explanatory power than the M7 model, except for banks, while the GUB model has worse monthly explanatory power than the M7 model.

However, the GUB model does not present statistically significant α values for any of the selected dates. In contrast, the M7 model

Table 8
Robustness analysis.

	M7 model								GUB model							
	Daily				Monthly				Daily				Monthly			
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
Agric	0.760	0.310	28.82%	− 6.075	0.656	0.467	56.96%	− 9.299	0.532	0.858	31.82%	− 1.240	0.499	0.700	60.77%	− 5.328
Food	0.533	0.218	63.02%	− 1.398	0.449	0.317	75.01%	− 17.200	0.515	0.831	63.04%	− 0.035	0.449	0.633	75.37%	− 8.230
Soda	0.661	0.272	32.56%	− 3.604	0.681	0.485	43.51%	− 9.328	0.740	1.192	32.49%	− 3.264	0.719	1.015	42.79%	− 4.604
Beer	0.572	0.232	32.57%	− 3.282	0.633	0.450	51.13%	− 5.700	0.720	1.156	31.93%	− 1.408	0.867	1.224	50.96%	− 4.628
Smoke	0.591	0.242	28.66%	− 5.971	0.612	0.436	35.73%	− 12.548	0.616	0.994	25.96%	− 3.171	0.810	1.146	32.80%	− 7.459
Toys	0.671	0.274	48.22%	− 8.607	0.673	0.475	67.19%	− 9.557	0.537	0.861	50.99%	− 3.801	0.499	0.702	73.15%	− 8.698
Fun	0.736	0.297	54.22%	− 4.478	0.685	0.484	73.49%	− 9.542	0.594	0.955	57.42%	− 3.446	0.624	0.884	77.13%	− 8.173
Books	0.548	0.224	55.78%	− 1.495	0.489	0.345	77.62%	− 6.316	0.528	0.853	58.49%	− 0.522	0.465	0.662	77.82%	− 4.118
Hshld	0.500	0.201	69.67%	− 4.065	0.231	0.165	82.96%	− 18.835	0.310	0.502	72.25%	− 0.419	0.196	0.276	86.22%	− 12.128
Clths	0.482	0.193	59.05%	− 2.490	0.428	0.306	74.31%	− 19.270	0.390	0.631	61.03%	− 2.257	0.402	0.568	75.84%	− 10.256
Hlth	0.707	0.288	59.85%	− 3.524	0.536	0.378	75.50%	− 9.835	0.578	0.937	60.67%	− 3.368	0.438	0.617	76.97%	− 5.988
MedEq	0.784	0.323	71.86%	− 3.603	0.832	0.589	79.85%	− 13.445	0.467	0.758	73.18%	− 2.552	0.412	0.582	80.63%	− 7.871
Drugs	0.841	0.342	76.20%	− 3.602	0.920	0.659	80.38%	− 14.421	0.416	0.670	70.88%	− 1.982	0.450	0.632	71.59%	− 7.699
Chems	0.537	0.216	71.13%	− 9.626	0.374	0.266	85.61%	− 34.930	0.285	0.461	73.85%	− 3.702	0.368	0.519	85.84%	− 12.508
Rubbr	0.635	0.261	51.16%	− 1.664	0.350	0.249	79.85%	− 15.538	0.454	0.732	52.56%	− 1.637	0.292	0.410	80.73%	− 9.462
Txtls	0.564	0.228	52.84%	− 2.401	0.796	0.561	69.87%	− 3.961	0.557	0.898	53.09%	− 2.192	0.692	0.971	69.89%	− 2.935
BldMt	0.541	0.222	67.04%	− 2.941	0.361	0.254	85.70%	− 23.727	0.294	0.476	74.00%	− 2.141	0.300	0.425	87.01%	− 14.540
Cnstr	0.505	0.204	58.58%	− 8.164	0.445	0.315	76.82%	− 19.777	0.444	0.711	60.83%	− 3.634	0.387	0.548	79.98%	− 12.253
Steel	0.602	0.245	69.30%	− 1.778	0.546	0.383	78.67%	− 14.330	0.583	0.940	71.51%	− 0.213	0.466	0.656	79.01%	− 5.912
FabPr	0.575	0.234	43.18%	− 5.384	0.577	0.407	67.94%	− 15.927	0.455	0.732	44.85%	− 2.915	0.561	0.789	70.69%	− 5.762
Mach	0.609	0.247	79.21%	− 2.566	0.414	0.294	88.63%	− 21.371	0.318	0.514	83.50%	− 2.414	0.407	0.570	90.66%	− 10.984
ElcEq	0.716	0.288	60.82%	− 5.078	0.505	0.354	82.53%	− 17.754	0.460	0.744	68.30%	− 1.606	0.494	0.693	86.41%	− 6.162
Autos	0.431	0.175	70.51%	− 1.056	0.588	0.414	84.16%	− 12.359	0.407	0.659	71.54%	− 1.093	0.529	0.746	84.42%	− 8.003
Aero	0.579	0.238	53.57%	− 1.056	0.447	0.319	66.74%	− 7.973	0.542	0.873	53.88%	− 0.941	0.416	0.588	68.84%	− 5.911
Ships	0.521	0.210	38.43%	− 3.523	0.664	0.473	57.96%	− 6.345	0.510	0.823	39.86%	− 3.039	0.617	0.868	59.58%	− 4.239
Guns	0.657	0.266	30.73%	− 1.012	0.718	0.509	47.54%	− 4.757	0.492	0.789	32.95%	− 0.158	0.489	0.691	49.79%	− 5.231
Gold	1.181	0.483	15.36%	− 2.747	1.390	0.985	26.82%	− 10.389	0.865	1.388	16.15%	− 2.165	0.973	1.372	28.20%	− 4.563
Mines	0.892	0.361	39.98%	− 1.451	1.189	0.841	53.06%	− 6.334	0.596	0.966	39.14%	− 1.117	0.986	1.390	53.08%	− 4.441
Coal	0.836	0.343	30.52%	− 1.359	1.011	0.720	37.03%	− 3.089	1.529	2.476	28.99%	− 0.786	1.061	1.499	31.73%	− 1.577
Oil	0.806	0.326	60.76%	− 5.680	0.831	0.589	60.90%	− 4.331	0.917	1.475	52.69%	− 5.932	0.983	1.385	48.07%	− 2.227
Util	0.359	0.147	63.16%	− 2.217	0.470	0.331	60.02%	− 14.086	0.544	0.877	51.13%	− 1.836	0.910	1.281	37.64%	− 6.817
Telcm	0.730	0.294	70.45%	− 2.887	0.796	0.562	80.17%	− 11.349	0.508	0.818	72.22%	− 2.258	0.777	1.100	77.90%	− 5.376
PerSv	0.611	0.251	50.24%	− 1.729	0.564	0.400	76.72%	− 12.053	0.451	0.728	55.91%	− 1.553	0.549	0.777	76.79%	− 7.820
BusSv	0.686	0.283	76.19%	− 2.027	0.491	0.348	89.53%	− 32.290	0.416	0.675	83.21%	− 0.404	0.299	0.425	91.52%	− 18.369
Hardw	0.768	0.313	78.91%	− 5.601	0.559	0.396	85.61%	− 10.807	0.533	0.858	77.55%	− 2.441	0.691	0.980	82.51%	− 5.734
Softw	0.722	0.295	61.64%	− 1.637	0.636	0.449	79.52%	− 12.326	0.514	0.826	69.08%	− 1.603	0.673	0.950	75.90%	− 6.486
Chips	0.780	0.316	83.08%	− 1.307	0.576	0.409	88.58%	− 10.727	0.382	0.613	82.56%	− 1.258	0.433	0.610	86.67%	− 5.650

(*continued on next page*)

Table 8 (*continued*)

	M7 model								GUB model							
	Daily				Monthly				Daily				Monthly			
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
LabEq	0.776	0.314	68.86%	− 4.461	0.571	0.403	86.23%	− 14.763	0.467	0.753	74.29%	− 2.521	0.458	0.647	86.67%	− 7.029
Paper	0.406	0.166	64.20%	− 1.793	0.427	0.303	82.59%	− 9.917	0.404	0.648	65.74%	− 1.232	0.457	0.647	80.40%	− 5.733
Boxes	0.489	0.198	49.79%	− 4.588	0.381	0.271	70.55%	− 15.410	0.468	0.757	52.52%	− 3.842	0.701	0.990	69.74%	− 10.044
Trans	0.507	0.206	68.72%	− 1.076	0.379	0.265	82.42%	− 23.188	0.347	0.558	71.21%	− 1.043	0.343	0.482	82.57%	− 17.242
Whlsl	0.614	0.251	74.19%	− 4.367	0.475	0.339	88.26%	− 21.786	0.322	0.518	79.67%	− 0.525	0.287	0.405	92.06%	− 12.165
Rtail	0.527	0.214	81.48%	− 2.178	0.440	0.311	83.16%	− 11.830	0.380	0.614	79.95%	− 0.230	0.532	0.748	81.21%	− 8.568
Meals	0.582	0.234	62.12%	− 7.096	0.363	0.260	75.86%	− 9.323	0.365	0.590	64.50%	− 0.044	0.344	0.488	77.31%	− 5.008
Banks	0.657	0.267	76.55%	− 1.092	0.440	0.314	81.51%	− 5.197	0.595	0.963	69.82%	− 1.007	0.777	1.106	69.46%	− 3.108
Insur	0.533	0.217	76.94%	− 6.145	0.361	0.257	85.51%	− 14.321	0.401	0.649	71.68%	− 0.154	0.642	0.914	75.79%	− 10.817
RlEst	0.664	0.272	43.77%	− 1.335	0.663	0.472	65.56%	− 10.924	0.609	0.986	45.51%	− 1.090	0.573	0.804	69.70%	− 10.661
Fin	0.683	0.279	78.06%	− 1.658	0.504	0.359	87.50%	− 9.756	0.485	0.786	78.77%	− 1.455	0.516	0.728	84.27%	− 7.046
Other	0.719	0.294	57.45%	− 3.127	0.653	0.465	73.65%	− 12.298	0.448	0.718	61.50%	− 2.581	0.534	0.753	79.67%	− 12.426

Note: Column (1) is the ratio $\frac{average(\alpha_i^2)}{average(r_i^2)}$, column (2) is the ratio $\frac{average[s^2(\alpha_i)]}{average(\alpha_i^2)}$, column (3) is the mean of the adjusted R^2 value, and column (4) is the mean of the out-of-sample R^2 value.

Table 9
Results of the *GRS* test.

Quartile	Date	OLS GRS test	*p*-Value	FGLS GRS test	*p*-Value
M7 Daily					
Min.	14-Jul-74	16.080	0.0055	15.171	0.0132
Median	21-Jun-95	16.593	0.0033	15.231	0.0125
Max.	10-Mar-83	17.339	0.0015	16.177	0.0050
M7 Monthly					
Min.	Jul-74	54.810	0.0032	40.183	0.0110
Median	Jul-94	55.996	0.0029	48.901	0.0051
Max.	Feb-83	100.349	0.0002	42.491	0.0089
GUB Daily					
Min.	14-Jul-74	13.397	0.0610	13.330	0.0643
Median	21-Jun-95	15.013	0.0153	14.550	0.0233
Max.	10-Mar-83	16.481	0.0037	15.540	0.0093
GUB Monthly					
Min.	Jun-74	25.342	0.0571	13.435	0.0647
Median	Jul-19	37.578	0.0142	35.663	0.0173
Max.	May-80	50.433	0.0045	47.095	0.0059

Table 10
Averages of daily significant β values.

Portfolios	M7 model							GUB model		
	Mkt-RF	SMB	HML	RMW	CMA	WML	QMJ	G	U	B
Agric	0.723(100%)	0.661(100%)	0.001(22%)	− 0.014(27%)	0.009(23%)	− 0.191(24%)	− 0.276(37%)	0.608(95%)	0.84(100%)	0.739(96%)
Food	0.711(100%)	0.489(100%)	0.118(72%)	− 0.012(63%)	0.207(46%)	− 0.041(72%)	0.175(57%)	0.473(94%)	0.674(100%)	0.595(100%)
Soda	0.758(100%)	0.413(97%)	0.071(41%)	0.026(35%)	0.368(35%)	0.046(32%)	0.243(34%)	0.817(77%)	0.697(95%)	0.765(90%)
Beer	0.696(100%)	0.463(86%)	0.027(43%)	0.181(13%)	0.349(42%)	− 0.054(54%)	0.34(35%)	0.532(75%)	0.712(100%)	0.587(94%)
Smoke	0.838(100%)	0.337(69%)	− 0.008(45%)	0.069(44%)	0.467(59%)	− 0.075(58%)	0.46(39%)	0.823(63%)	0.809(99%)	0.678(78%)
Toys	0.806(100%)	0.74(100%)	0.069(37%)	0.132(49%)	0.292(22%)	− 0.13(55%)	− 0.275(50%)	0.736(92%)	0.884(100%)	0.818(100%)
Fun	0.797(100%)	0.708(100%)	− 0.011(37%)	− 0.093(36%)	0.089(23%)	− 0.122(56%)	− 0.311(62%)	0.727(99%)	0.875(100%)	0.876(100%)
Books	0.794(100%)	0.685(100%)	0.198(70%)	− 0.016(54%)	0.291(36%)	− 0.114(59%)	0.176(48%)	0.655(100%)	0.816(100%)	0.729(97%)
Hshld	0.85(100%)	0.704(100%)	0.16(53%)	0.089(55%)	0.186(64%)	− 0.121(76%)	0.032(62%)	0.725(100%)	0.84(100%)	0.767(100%)
Clths	0.867(100%)	0.804(100%)	0.277(62%)	0.139(69%)	0.169(35%)	− 0.14(86%)	0.101(61%)	0.698(97%)	0.863(100%)	0.753(100%)
Hlth	0.845(100%)	0.843(100%)	− 0.177(64%)	− 0.168(40%)	− 0.017(36%)	− 0.105(35%)	− 0.318(56%)	0.811(100%)	0.925(100%)	0.917(100%)
MedEq	0.857(100%)	0.799(100%)	− 0.273(71%)	− 0.222(71%)	0.051(49%)	− 0.082(42%)	− 0.299(53%)	0.845(100%)	0.902(100%)	0.985(100%)
Drugs	0.925(100%)	0.747(100%)	− 0.555(92%)	− 0.491(84%)	0.199(52%)	− 0.006(55%)	− 0.369(93%)	1.051(100%)	1.028(100%)	1.128(100%)
Chems	0.938(100%)	0.625(100%)	0.052(64%)	0.105(46%)	0.154(82%)	− 0.116(74%)	− 0.261(49%)	0.714(100%)	0.979(100%)	0.796(100%)
Rubbr	0.787(100%)	0.771(100%)	0.183(35%)	− 0.016(38%)	0.217(64%)	− 0.127(53%)	0.1(30%)	0.711(97%)	0.782(100%)	0.745(100%)
Txtls	0.846(100%)	0.82(100%)	0.359(64%)	0.119(32%)	0.256(48%)	− 0.156(69%)	0.07(51%)	0.706(99%)	0.857(100%)	0.756(99%)
BldMt	0.867(100%)	0.796(100%)	0.197(80%)	0.076(49%)	0.11(70%)	− 0.124(89%)	− 0.018(65%)	0.739(100%)	0.869(100%)	0.762(100%)
Cnstr	0.983(100%)	0.888(100%)	0.206(82%)	0.216(46%)	− 0.021(45%)	− 0.129(58%)	− 0.318(64%)	0.892(100%)	1.049(100%)	0.875(100%)
Steel	1.044(100%)	0.785(100%)	0.217(81%)	0.033(81%)	0.075(74%)	− 0.182(85%)	− 0.392(57%)	0.882(100%)	1.1(100%)	0.876(100%)
FabPr	0.848(100%)	0.834(100%)	0.202(68%)	0.098(18%)	− 0.008(25%)	− 0.121(36%)	− 0.174(37%)	0.755(100%)	0.924(100%)	0.745(94%)
Mach	0.951(100%)	0.793(100%)	0.054(70%)	− 0.077(54%)	0.057(69%)	− 0.118(83%)	− 0.139(54%)	0.89(100%)	0.959(100%)	0.897(100%)
ElcEq	0.873(100%)	0.81(100%)	− 0.033(55%)	− 0.215(50%)	0.099(52%)	− 0.092(70%)	− 0.088(77%)	0.793(95%)	0.956(100%)	0.873(100%)
Autos	1.029(100%)	0.785(100%)	0.214(91%)	0.13(75%)	0.232(53%)	− 0.18(93%)	− 0.114(63%)	0.861(100%)	1.044(100%)	0.851(100%)
Aero	0.962(100%)	0.592(100%)	0.168(54%)	0.214(33%)	0.216(48%)	− 0.054(64%)	− 0.136(30%)	0.797(92%)	0.982(100%)	0.842(96%)
Ships	0.969(100%)	0.802(100%)	0.26(47%)	0.147(29%)	0.263(32%)	− 0.108(62%)	0.045(37%)	0.81(95%)	1.058(99%)	0.836(91%)
Guns	0.837(100%)	0.594(100%)	0.237(34%)	0.033(37%)	0.21(18%)	0.097(40%)	0.071(20%)	0.771(73%)	0.996(97%)	0.77(86%)
Gold	0.416(69%)	0.578(76%)	− 1.032(66%)	− 0.262(67%)	0.276(67%)	0.111(76%)	− 1.32(88%)	0.921(69%)	0.835(70%)	0.696(60%)
Mines	0.825(100%)	0.627(100%)	− 0.279(66%)	0.008(77%)	0.064(61%)	− 0.024(63%)	− 0.939(78%)	0.918(81%)	1.09(100%)	0.87(84%)
Coal	0.976(100%)	0.616(98%)	− 0.216(64%)	0.561(62%)	− 0.558(44%)	− 0.109(67%)	− 1.432(66%)	1.346(96%)	1.196(94%)	1.074(93%)
Oil	0.872(100%)	0.55(100%)	− 0.146(85%)	0.378(87%)	− 0.014(72%)	− 0.064(78%)	− 1.093(96%)	0.964(83%)	1.01(100%)	0.95(98%)
Util	0.644(100%)	0.203(95%)	0.357(87%)	0.08(82%)	0.087(83%)	− 0.001(84%)	− 0.071(69%)	0.448(77%)	0.531(100%)	0.434(88%)
Telcm	0.892(100%)	0.659(100%)	− 0.077(61%)	− 0.117(46%)	0.138(52%)	− 0.12(72%)	− 0.408(77%)	0.948(100%)	0.973(100%)	0.967(100%)
PerSv	0.815(100%)	0.83(100%)	0.072(46%)	0.083(45%)	0.12(28%)	− 0.077(67%)	− 0.032(50%)	0.709(100%)	0.857(100%)	0.781(99%)
BusSv	0.833(100%)	0.808(100%)	− 0.133(40%)	− 0.133(62%)	0.073(51%)	− 0.072(57%)	− 0.189(64%)	0.816(100%)	0.862(100%)	0.908(100%)
Hardw	1.042(100%)	0.828(100%)	− 0.316(86%)	− 0.343(92%)	− 0.145(71%)	− 0.15(75%)	− 0.264(45%)	1.242(100%)	1.174(100%)	1.141(100%)

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Table 10 (*continued*)

Portfolios	M7 model							GUB model		
	Mkt-RF	SMB	HML	RMW	CMA	WML	QMJ	G	U	B
Softw	0.945(100%)	0.898(100%)	− 0.308(75%)	− 0.438(67%)	− 0.258(69%)	− 0.018(55%)	− 0.494(55%)	1.27(100%)	1.06(100%)	1.222(100%)
Chips	0.987(100%)	0.884(100%)	− 0.251(76%)	− 0.428(86%)	− 0.104(57%)	− 0.082(84%)	− 0.151(65%)	1.178(100%)	1.084(100%)	1.114(100%)
LabEq	0.878(100%)	0.828(100%)	− 0.196(62%)	− 0.327(68%)	0.126(43%)	− 0.099(57%)	− 0.077(52%)	0.891(100%)	0.947(100%)	0.92(100%)
Paper	0.888(100%)	0.649(100%)	0.213(87%)	0.019(50%)	0.156(73%)	− 0.145(61%)	0.218(50%)	0.673(100%)	0.872(100%)	0.739(100%)
Boxes	0.931(100%)	0.643(100%)	0.233(55%)	0.194(50%)	0.304(54%)	− 0.134(65%)	0.087(45%)	0.71(92%)	0.942(100%)	0.767(94%)
Trans	0.92(100%)	0.713(100%)	0.221(68%)	0.203(45%)	0.136(69%)	− 0.136(81%)	− 0.255(61%)	0.772(100%)	0.972(100%)	0.789(100%)
Whlsl	0.8(100%)	0.775(100%)	0.048(63%)	− 0.01(59%)	0.147(61%)	− 0.081(86%)	− 0.085(74%)	0.762(100%)	0.789(100%)	0.818(100%)
Rtail	0.933(100%)	0.811(100%)	0.153(80%)	0.164(57%)	0.149(60%)	− 0.13(92%)	0.093(72%)	0.772(100%)	0.921(100%)	0.815(100%)
Meals	0.825(100%)	0.741(100%)	0.034(66%)	0.195(63%)	0.158(59%)	− 0.118(65%)	− 0.16(46%)	0.713(100%)	0.868(100%)	0.76(100%)
Banks	0.65(100%)	0.528(100%)	0.388(100%)	− 0.021(83%)	− 0.159(63%)	− 0.099(83%)	0.002(80%)	0.571(100%)	0.604(100%)	0.559(100%)
Insur	0.774(100%)	0.506(100%)	0.277(98%)	− 0.21(82%)	− 0.101(44%)	− 0.054(66%)	0.212(61%)	0.597(100%)	0.719(100%)	0.672(100%)
RlEst	0.725(100%)	0.749(100%)	0.206(40%)	0.147(43%)	0.083(42%)	− 0.166(68%)	− 0.34(53%)	0.861(91%)	0.771(100%)	0.775(89%)
Fin	0.729(100%)	0.574(100%)	0.233(83%)	− 0.09(72%)	− 0.154(61%)	− 0.104(81%)	− 0.085(75%)	0.706(100%)	0.701(100%)	0.693(100%)
Other	0.749(100%)	0.742(100%)	− 0.069(55%)	− 0.062(43%)	0.162(29%)	− 0.048(66%)	− 0.226(82%)	0.782(100%)	0.779(100%)	0.848(99%)

Table 11
Averages of monthly significant β values.

Portfolios	M7 model							GUB model		
	Mkt-RF	SMB	HML	RMW	CMA	WML	QMJ	G	U	B
Agric	0.758(85%)	1.065(92%)	− 0.255(22%)	− 1.355(9%)	1.203(23%)	− 0.078(23%)	− 0.769(8%)	0.026(83%)	0.87(74%)	0.021(78%)
Food	0.718(100%)	0.577(88%)	0.221(22%)	0.186(21%)	0.154(29%)	− 0.128(35%)	− 0.11(13%)	0.011(82%)	0.695(100%)	0.016(92%)
Soda	0.902(86%)	0.794(47%)	0.447(25%)	1.219(10%)	0.001(7%)	− 0.358(27%)	0.585(13%)	0.019(32%)	0.787(57%)	0.019(54%)
Beer	0.741(94%)	0.754(37%)	− 0.105(31%)	− 1.065(9%)	0.332(12%)	− 0.117(18%)	0.823(11%)	0.015(41%)	0.669(65%)	0.018(83%)
Smoke	0.921(83%)	0.438(39%)	− 0.67(19%)	1.725(13%)	2.243(23%)	− 0.225(18%)	− 0.401(6%)	0.018(23%)	0.704(34%)	0.018(42%)
Toys	0.916(88%)	1.039(85%)	− 0.286(13%)	0.776(8%)	0.953(23%)	− 0.338(43%)	− 0.971(25%)	0.024(92%)	1.066(98%)	0.023(88%)
Fun	0.865(87%)	1.01(91%)	− 0.441(19%)	0.33(20%)	− 0.019(13%)	− 0.214(37%)	− 1.143(42%)	0.022(98%)	1.018(100%)	0.023(95%)
Books	0.897(100%)	0.795(88%)	0.475(13%)	0.519(20%)	0.999(30%)	− 0.256(29%)	− 0.41(40%)	0.018(96%)	0.969(100%)	0.02(91%)
Hshld	0.911(100%)	0.888(100%)	0.271(20%)	0.002(30%)	0.171(8%)	− 0.275(38%)	0.04(23%)	0.02(96%)	0.974(100%)	0.02(93%)
Clths	0.871(100%)	1.027(99%)	0.397(25%)	0.84(34%)	0.83(16%)	− 0.263(46%)	− 0.516(13%)	0.02(90%)	0.992(100%)	0.021(90%)
Hlth	0.891(100%)	1.069(100%)	− 0.784(23%)	0.214(15%)	0.51(8%)	− 0.22(10%)	− 0.63(32%)	0.022(92%)	1.207(100%)	0.022(90%)
MedEq	0.81(96%)	1.038(97%)	− 0.688(52%)	− 0.735(41%)	− 0.065(10%)	− 0.183(21%)	− 0.368(44%)	0.023(95%)	1.172(100%)	0.021(97%)
Drugs	0.865(97%)	0.906(98%)	− 1.017(68%)	− 1.041(47%)	1.279(10%)	− 0.095(17%)	− 0.925(56%)	0.025(91%)	1.356(98%)	0.023(84%)
Chems	0.981(100%)	0.667(100%)	0.055(28%)	0.226(25%)	0.514(23%)	− 0.303(37%)	− 0.532(47%)	0.018(99%)	0.957(100%)	0.022(99%)
Rubbr	0.932(100%)	1.071(100%)	0.476(26%)	0.731(26%)	0.452(17%)	− 0.258(30%)	− 0.109(30%)	0.02(99%)	0.995(100%)	0.022(94%)
Txtls	0.924(95%)	1.025(99%)	0.475(32%)	1.022(37%)	0.752(24%)	− 0.339(32%)	− 0.306(27%)	0.021(79%)	0.951(88%)	0.024(93%)
BldMt	0.94(100%)	0.963(100%)	0.499(18%)	0.091(38%)	0.627(22%)	− 0.214(48%)	− 0.297(56%)	0.022(98%)	1.009(100%)	0.021(97%)
Cnstr	1.042(100%)	1.163(98%)	0.533(31%)	− 0.5(18%)	1.099(16%)	− 0.172(35%)	− 0.322(32%)	0.028(99%)	1.128(97%)	0.022(94%)
Steel	1.078(100%)	0.926(98%)	0.251(37%)	0.098(23%)	0.104(42%)	− 0.404(43%)	− 0.918(35%)	0.025(94%)	1.139(100%)	0.024(92%)
FabPr	0.882(100%)	1.059(93%)	0.536(11%)	0.362(19%)	0.175(6%)	− 0.326(26%)	− 0.926(14%)	0.023(98%)	1.051(97%)	0.021(85%)
Mach	0.983(100%)	0.914(100%)	− 0.091(15%)	0.221(19%)	0.514(11%)	− 0.23(60%)	− 0.697(26%)	0.021(100%)	1.095(100%)	0.023(100%)
ElcEq	0.949(100%)	0.94(100%)	− 0.29(30%)	− 0.422(3%)	0.377(3%)	− 0.252(24%)	− 0.109(28%)	0.022(100%)	1.186(100%)	0.022(96%)
Autos	1.071(100%)	0.963(100%)	0.45(43%)	0.043(35%)	0.37(40%)	− 0.344(56%)	− 0.331(33%)	0.024(97%)	1.063(100%)	0.025(93%)
Aero	1(100%)	0.917(88%)	0.75(6%)	− 0.23(22%)	− 0.972(3%)	0.162(25%)	0.962(16%)	0.021(84%)	1.019(89%)	0.022(87%)
Ships	1.003(100%)	1.06(82%)	0.789(6%)	0.129(27%)	0.683(6%)	− 0.142(24%)	− 0.993(20%)	0.024(87%)	1.078(85%)	0.024(66%)
Guns	0.851(76%)	0.865(65%)	0.716(22%)	0.851(12%)	− 1.825(12%)	0.161(19%)	− 0.951(8%)	0.019(71%)	1.009(79%)	0.018(60%)
Gold	0.861(18%)	1.248(30%)	− 1.725(42%)	− 1.19(28%)	2.07(24%)	0.488(15%)	− 2.844(47%)	0.028(34%)	1.042(19%)	0.023(30%)
Mines	0.898(84%)	0.812(39%)	− 0.655(35%)	− 1.147(24%)	0.351(30%)	− 0.322(41%)	− 1.827(57%)	0.027(68%)	1.043(67%)	0.023(67%)
Coal	1.194(68%)	1.12(24%)	− 1.08(23%)	1.086(27%)	− 0.436(26%)	− 0.285(22%)	− 3.105(36%)	0.032(34%)	1.207(52%)	0.037(45%)
Oil	0.821(85%)	0.692(38%)	− 0.477(51%)	1.239(42%)	0.992(31%)	− 0.059(39%)	− 2.326(74%)	0.021(55%)	1.041(69%)	0.026(72%)
Util	0.613(100%)	0.119(10%)	0.543(53%)	0.081(16%)	− 0.182(46%)	0.074(35%)	− 0.541(25%)	0.007(25%)	0.443(67%)	0.01(55%)
Telcm	0.856(95%)	0.685(87%)	− 0.269(29%)	0.368(13%)	− 0.224(27%)	− 0.258(43%)	− 1.127(49%)	0.025(86%)	1.167(100%)	0.021(91%)
PerSv	0.842(99%)	1.013(100%)	− 0.155(12%)	0.943(22%)	0.684(11%)	− 0.291(27%)	− 0.864(26%)	0.021(97%)	0.987(100%)	0.021(91%)
BusSv	0.876(100%)	0.972(100%)	− 0.485(28%)	− 0.487(25%)	0.073(18%)	− 0.189(27%)	− 0.672(33%)	0.022(100%)	1.114(100%)	0.022(98%)

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Table 11 (*continued*)

Portfolios	M7 model							GUB model		
	Mkt-RF	SMB	HML	RMW	CMA	WML	QMJ	G	U	B
Hardw	1.071(100%)	1.159(99%)	− 0.591(65%)	− 0.881(37%)	0.442(20%)	− 0.407(54%)	− 0.007(19%)	0.033(100%)	1.399(100%)	0.025(94%)
Softw	0.937(97%)	1.126(100%)	− 0.874(68%)	− 0.802(37%)	0.543(24%)	− 0.347(22%)	− 0.54(15%)	0.031(96%)	1.388(97%)	0.025(90%)
Chips	1.019(100%)	1.129(100%)	− 0.502(47%)	− 0.883(39%)	− 0.163(20%)	− 0.208(45%)	− 0.622(14%)	0.03(100%)	1.416(100%)	0.025(94%)
LabEq	0.913(100%)	1.066(100%)	− 0.434(33%)	− 0.704(20%)	0.313(11%)	− 0.228(37%)	− 0.415(29%)	0.025(100%)	1.179(100%)	0.023(99%)
Paper	0.943(100%)	0.645(92%)	0.305(29%)	0.346(22%)	0.513(17%)	− 0.285(50%)	0.116(31%)	0.017(98%)	0.892(100%)	0.02(94%)
Boxes	0.993(100%)	0.854(87%)	0.349(3%)	0.332(24%)	0.705(15%)	− 0.316(31%)	0.282(23%)	0.018(81%)	0.842(92%)	0.023(89%)
Trans	0.953(100%)	0.853(99%)	0.501(31%)	0.189(29%)	0.024(21%)	− 0.241(37%)	0.108(17%)	0.02(96%)	0.967(100%)	0.021(90%)
Whlsl	0.832(100%)	1.005(100%)	− 0.168(29%)	0.119(37%)	0.515(18%)	− 0.261(33%)	− 0.506(51%)	0.022(100%)	1.028(100%)	0.021(98%)
Rtail	0.979(100%)	1.012(100%)	0.35(22%)	0.578(33%)	0.498(26%)	− 0.325(64%)	0.364(29%)	0.021(97%)	1.024(100%)	0.021(89%)
Meals	0.849(100%)	0.994(98%)	− 0.054(24%)	0.522(28%)	0.497(24%)	− 0.309(41%)	− 0.235(19%)	0.019(90%)	0.916(97%)	0.022(93%)
Banks	0.756(100%)	0.561(90%)	0.688(88%)	0.211(47%)	− 0.365(27%)	− 0.21(33%)	− 0.566(30%)	0.015(79%)	0.652(90%)	0.015(88%)
Insur	0.845(100%)	0.557(95%)	0.465(64%)	− 0.27(49%)	− 0.482(20%)	− 0.064(35%)	0.087(43%)	0.012(78%)	0.803(100%)	0.016(92%)
RlEst	0.889(91%)	1.052(82%)	0.765(23%)	0.327(14%)	0.355(31%)	− 0.431(28%)	− 0.944(24%)	0.024(82%)	0.921(86%)	0.022(88%)
Fin	0.789(100%)	0.605(100%)	0.449(65%)	0.238(8%)	− 0.331(24%)	− 0.14(46%)	− 0.557(40%)	0.017(95%)	0.79(100%)	0.018(94%)
Other	0.769(100%)	0.83(97%)	− 0.56(25%)	0.595(13%)	0.907(16%)	− 0.173(17%)	− 0.948(46%)	0.021(99%)	1.014(97%)	0.021(95%)

produces significant α values for most of the dates. Finally, while the GUB model shows statistically significant β values for all the factors (GUB) for all the selected dates, in the case of the M7 model, only the market factor (Mkt-Rf) is significant in all cases (except for gold at the daily frequency). Therefore, although we have selected specific dates when the M7 model presents greater explanatory power for the excess return of the industrial portfolios, the results show that the GUB model is more consistent.

4.6. *Analysis of the relationship between the GUB and M7 factors*

In this section, we analyze whether the information contained in the GUB factors is similar to that contained in the M7 factors. This issue is relevant because, if not, the explanatory capacity of the GUB model could even be improved by incorporating some of the M7 factors. For this purpose, we first study whether the GUB factors explain the M7 factors. Table 14 shows the rolling regression results for both frequencies. We report the average value of the statistically significant parameters and, in brackets, the percentages of cases in which each parameter is significant.

In Table 14, we note that the R^2 values are low for all the M7 factors except Mkt-Rf. In addition, it is worth noting that each of the M7 factor has a different weight and percentage of significant cases for each GUB factor.

For the daily frequency, we observe that the GUB factor weights are different for each M7 factor, so these latter factors represent good and bad news and usual market behavior differently: Mkt-Rf presents a usual β with a value of 0.99, but low and equal βs for the good and bad factors; SMB shows a bad β higher than the good β, while the usual β is low; the HML β values are similar for the three GUB factors and negative. For WML, only the good β values are significant; RMW shows that the good β is higher than the bad β; CMA has a higher good negative β than the others factors, and, for QMJ, the β is negative and the bad β is the highest. Moreover, the percentage of significant cases for the daily data is higher than for the monthly data, although only for SMB is there a significant

Table 12
Analysis of the regression residuals.

Model	Frequency	Max. value	Min. value
Autoregression on raw data			
M7	Daily	441.133**	19.762**
GUB	Daily	63.902**	29.231
M7	Monthly	18.280	0.0029
GUB	Monthly	12.560	0.0018
Autoregression on squared data			
M7	Daily	1280.225**	82.862**
GUB	Daily	73.411**	3.851*
M7	Monthly	29.826	0.0032
GUB	Monthly	28.164	0.0031
Heteroscedasticity			
M7	Daily	929.982**	70.977**
GUB	Daily	41.795**	74.075
M7	Monthly	29.115	0.0089
GUB	Monthly	26.493	0.0001

Note: ** and * indicate that the null hypothesis (non-autoregressive raw or squared data and no heteroscedasticity) is rejected at the 1% and 5% confidence levels, respectively.

Table 13
Point comparison.

Portf.	Date	M7 model									GUB model				
		Adj. R^2	Alpha	Mkt-Rf	SMB	HML	WML	RMW	CMA	QMJ	adj. R^2	Alpha	Good	Usual	Bad
Daily worst cases of adjusted R^2															
Gold	26-Mar-03	1.19%	0.002*	− 0.21	0.16	− 0.39	0.12	0.33	0.06	− 0.62**	8.86%	− 0.011	1.97**	− 0.87**	1.04**
Coal	12-Oct-95	1.83%	0.001*	0.57**	0.69**	0.09	0.2	0.11	− 0.01	− 0.57	6.22%	− 0.002	1.67**	0.75**	0.83*
Soda	26-Sep-97	3.12%	0.002**	0.51**	0.22	− 0.45	− 0.12	0.48*	− 0.12	− 0.58	12.63%	− 0.008	1.47**	0.64*	1.77**
Daily best cases of adjusted R^2															
Banks	29-Jun-20	93.81%	0.003**	0.81**	0.76**	0.88**	− 0.43**	− 0.45**	0.068**	0.54**	85.51%	0.001	1.11**	0.72**	1.06**
Fin	12-Jul-13	94.13%	0.003*	0.91**	0.53**	0.12**	− 0.48**	− 0.26**	− 0.121**	− 0.02	95.73%	− 0.004	1.12**	1.01**	0.98**
Mach	30-Sep-13	94.94%	0.002*	1.09**	0.79**	− 0.21**	− 0.06	0.01	− 0.197**	− 0.21**	95.59%	− 0.002	1.17**	1.19**	1.18**
Monthly worst cases of adjusted R^2															
Gold	Dec-92	4.57%	0.007	− 0.41	0.25	0.12	− 0.14	0.13	0.177	− 1.73	9.63%	− 0.001	1.42**	0.92**	− 1.96**
Coal	Sep-00	5.12%	− 0.007	0.83**	− 0.03	0.02	− 0.44	1.08*	− 0.057	0.04	11.04%	0.008	− 1.26**	0.92**	0.74**
Soda	Sep-96	5.31%	0.001	0.59*	0.07	0.04	0.52	0.41	− 0.088	− 0.35	16.27%	0.004	− 1.43**	1.38**	0.71**
Monthly best cases of adjusted R^2															
Banks	Jun-20	93.81%	0.002*	0.53**	0.34	0.54*	− 0.48	− 0.08	0.098	− 0.03	91.37%	0.009	− 1.81**	0.86**	1.86**
Fin	Oct-79	96.55%	0.008**	0.61**	0.19**	0.32*	0.23	− 0.08	− 0.097	− 0.81**	96.06%	− 0.001	− 1.35**	0.75**	1.63**
Mach	Oct-76	97.41%	0.003*	0.77**	1.01**	0.38*	− 0.45	− 0.15	− 0.081	0.08	96.52%	0.004	− 0.57**	1.56**	− 0.77**

Note: ** and * indicate that the parameter is different from zero at the 1% and 5% confidence levels, respectively; α values are expressed in 1.0E − 2.

Table 14
Relationship among the GUB and M7 factors.

Factors	Adj. R^2	Constant	Good	Usual	Bad	Improve R^2 GUB + factor
Daily data						
Mkt-Rf	74.05%	− 0.0005(0%)	0.755(100%)	0.99(100%)	0.756(100%)	0.89%
SMB	15.61%	0.0003(100%)	0.125(100%)	0.049(100%)	0.222(100%)	0.75%
HML	22.77%	0.0004(0%)	− 0.182(100%)	− 0.154(100%)	− 0.175(100%)	1.55%
WML	15.23%	0.0003(100%)	− 0.174(100%)	0(0%)	0(0%)	1.12%
RMW	14.38%	0.0004(0%)	− 0.222(100%)	− 0.091(100%)	− 0.171(100%)	0.71%
CMA	14.84%	0.0008(100%)	− 0.27(100%)	− 0.012(100%)	0.06(100%)	0.74%
QMJ	29.30%	0.0004(100%)	− 0.215(100%)	− 0.168(100%)	− 0.231(100%)	0.82%
Monthly data						
Mkt-Rf	75.89%	0.005(37%)	0.011(80%)	0.815(100%)	0.015(98%)	0.92%
SMB	42.32%	− 0.001(28%)	0.009(86%)	0.319(79%)	0.008(67%)	0.78%
HML	18.02%	0.007(38%)	− 0.004(58%)	− 0.255(59%)	− 0.002(26%)	1.58%
WML	20.69%	0.008(62%)	− 0.009(40%)	− 0.167(54%)	− 0.003(39%)	1.19%
RMW	15.02%	0.005(44%)	− 0.001(30%)	− 0.193(57%)	− 0.004(37%)	0.82%
CMA	25.71%	0.014(75%)	− 0.014(70%)	− 0.055(22%)	− 0.002(52%)	0.83%
QMJ	46.67%	0.008(73%)	− 0.007(78%)	− 0.285(66%)	− 0.008(75%)	0.91%

Table 15
Risk premiums.

Factors	Lambda	*t*-Prob.
DAILY		
Mkt-Rf	0.00044	0.007
SMB	0.00034	0.009
HML	−0.00002	0.811
RMW	−0.00023	0.994
CMA	0.00029	0.006
WML	0.00026	0.103
QMJ	−0.00011	0.822
Mean adj. R^2	51.38%	
Good	−0.00020	0.108
Usual	0.00039	0.005
Bad	0.00049	0.007
Mean adj. R^2	43.36%	
MONTHLY		
Mkt-Rf	0.0072	0.004
SMB	0.0023	0.061
HML	0.0003	0.731
RMW	−0.0014	0.893
CMA	0.5090	0.358
WML	−0.0028	0.469
QMJ	−0.0025	0.962
Mean adj. R^2	58.68%	
Good	−0.0511	0.087
Usual	0.0061	0.008
Bad	0.1685	0.049
Mean adj. R^2	48.23%	

increase in the explanatory power of the GUB factors with decreasing data frequency (monthly).

Since the low R^2 results indicate that the information provided by the GUB factors is different from that provided by the M7 factors, we study whether adding each of the latter seven factors to the GUB model would substantially improve its explanatory power. The last column of Table 14 shows the improvement in the explanatory power for the industrial portfolios from incorporating the corresponding M7 factor to the GUB model. Note that these improvements are very small.

In short, except for Mkt-Rf, the GUB model is inadequate in explaining the other M6 factors, although, for the daily frequency, this model indicates which type of news influences each of the M6 factors the most. Our aim, however, is not to explain the M7 factors, but, rather, to replace them, to explain the industrial portfolios with fewer anomalies than for the M7 model.

4.7. Analysis of the risk premiums

Finally, we estimate the risk premiums from our previously calculated betas for the M7 and GUB models, following Fama and MacBeth (1973):

$$r_{t+1} = \lambda_{0,t} + \sum_{j=1}^{J} \lambda_{j,t} \cdot \beta_{j,t} + \zeta_t \tag{3}$$

The expression (3) is estimated in the cross section, and the risk premium is then calculated as $\overline{\lambda_j} = \frac{\lambda_{j,t}}{H}$, where H is the number of cross-sectional regressions. The standard errors are estimated following Newey and West (1987). Table 15 shows the results of the risk premiums for both frequencies.

The significant risk premiums for the M7 model are those for Mkt-Rf, SMB, and CMA at the 1% confidence level and daily frequency. At the monthly frequency, only Mkt-Rf (at the 1% level) and SMB (at the 10% level) are statistically significant. The sign of the significant premiums is as expected (positive), since the greater the sensitivity to risk (β), the higher the expected excess return.

For the GUB model, we observe that the usual factor shows significant risk premiums similar to Mkt-Rf for both frequencies. The risk premiums of the bad factor are statistically significant and higher than the usual and good factors; therefore, the higher the bad β, the higher the expected excess return. This result is consistent with expectations, since the greater the risk (weight of bad news), the higher the expected return. Finally, the risk premium of the good factor is negative (the higher the good β, the lower the expected excess return) and significant at 10%. This result indicates that, if a portfolio is more positively sensitive to good news at time t, the expected returns for the following period $(t+1)$ are lower. These results is also financially consistent. They provide empirical evidence on investors' risk aversion and their asymmetric behavior.

5. Conclusions

There is a vast literature on factor asset pricing models, but there is little consensus on the most accurate factors for explaining asset returns with low anomalies (where α is statistically significant) and including investors' risk aversion. Therefore, some of the financial literature has focused on analyzing and cataloging the anomalies of these models and using moments of order higher than two to model asset return behavior. In this context, our main contribution is to study a new type of anomaly, called statistical anomalies, that supports the evidence on asymmetric investor behavior observed in the face of upward and downward market movements.

Following the proposed time series decomposition of González-Sánchez (2021), we build three factors with positive outliers (the good), negative outliers (the bad), and the remainder of the Gaussian data (the usual). Then, to check if there are statistical anomalies, we arranged a horse race between the magnificent seven factors model (Mkt-Rf, SMB, HML, RMW, WML, CMA, and QMJ) and the GUB factors model. For a sample that consists of 49 industrial US portfolios from July 1969 to June 2020, at daily and monthly frequencies, we estimate more than 2 million and 500,000 rolling regressions for the daily and monthly data, respectively.

First, using PCA, we find that the M7 factors' covariance matrix has multicollinearity issues, while the covariance matrix for the GUB factors does not show any problems. We also note that the usual factor is very similar to the Mkt-Rf factor (see Fig. 1), while the other six factors are a combination of the good and bad factors, but with a lower R^2, and, then, they are not complementary, since the improvement in R^2 obtained by incorporating each of these factors into the GUB model is negligible.

Our main contribution is in finding that the number of anomalies (number of times alpha is significant at the 5% and 1% confidence levels) decreases substantially for all the portfolios and frequencies for the GUB model with respect to the M7 model (54% and 46%, on average, for the daily and monthly frequencies, respectively). In addition, we find that the results of the α ratios indicate that the performance of the GUB model is better than the M7 model (see Table 8).

Regarding the goodness of fit (R^2) of the models, the M7 model only shows better daily performance than the GUB model for six industrial portfolios, and 14 of them for the monthly frequency. In addition, standard robustness tests for both models (M7 vs. GUB) show better results for the GUB model than for the M7 model. We also compare the robustness of the models by analyzing their results for specific dates (i.e., when the M7 model shows the three best and three worst levels of explanatory power, or the adjusted R^2). The results indicate that the explanatory power of the GUB model is higher than that of the M7 model, except for the banks, finance, and machinery industrial portfolios at the monthly frequency. We also find that the weights (β) of the factors in explaining the returns of the industrial portfolios for the GUB model show a higher percentage of cases with statistical significance than for the M7 model. At the daily frequency, the residuals of the M7 model exhibit autoregression and heteroscedasticity, and the GUB model residuals do not.

Finally, we find that the risk premiums for the M7 model are significant only for Mkt-Rf, SMB, and CMA at the daily frequency and for Mkt-Rf and SMB at the monthly frequency. However, for the GUB model, we observe that the usual factor shows significant risk premiums similar to Mkt-Rf for both frequencies, and the risk premiums of the bad factor are statistically significant and higher than for the usual and good factors; so the higher the bad β, the higher the expected excess return. This last result provides evidence of one of the stylized facts of asset returns, their negative skewness (overreaction to bad news), and provides support for investor risk aversion.

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