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The examination of Fama-French Model during the Covid-19

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ABSTRACT

This paper evaluates the performance of Fama-French models on US stock markets during the selected events by studying the $R^2$ of the models. We find that the influence of Dotcom bubble to the $R^2$ of growth model is statistically significant. The $R^2$ of growth portfolios decreases rapidly during the Financial crisis of 2008. The latest Covid-19 outbreak drop has led to a substantial in the $R^2$ during this event. Furthermore, we find that all of the beta model parameters are insignificant in the GMM model.

1. Introduction

The central issue of empirical finance is predicting stock returns, in which the core is how the stocks behave during crises. Fama & French (1993) extend the capital asset price model (CAPM) and contribute to the beta factor significance. For example, book-to-market value of particular company and the size of the firms both have great significances in explaining the returns of stocks. Fama & French (2016) follow Miller & Modigliani (1961) to add two new factors, the profitability (RMW) and investment (CMA) strategy of the companies. The new model achieves better results in explaining the excess returns of stocks, between 71% and 94% based on $R^2$. To the best of our knowledge, there are just few papers that examine Fama-French model during the crises on stock markets. The main focus of this paper therefore aims at how the ability of the model to explain the excess returns of selected stocks during the crises, including Covid-19.

According to Fabozzi & Francis (1978), the stock’s beta coefficient varies randomly over time. The finding contradicts to the basic CAPM model assumptions. Bos & Newbold (1984) suggest that beta depends on microeconomic factors such as business environment of the company or the revised expectations by management as well as on macroeconomic factors such as inflation rate or stage of the economy business cycle. Fama & French (2016) consider that the possible influencing factors of excess returns are systematic risk measure $\beta$, size of the firm (SMB), and book-to-market factor (HML). In addition, they conclude that $\beta$ is not a sufficient parameter for explanation of returns variability and does not assist with explaining the cross-section average returns of stocks. Fama & French (2007) argue that there may be unusual financial pressure on value stocks that only occur during periods of very severe financial crises.

The close study is Racicot, Rentz, Kahl & Mesly (2019). The authors use a recursive/rolling robust instrumental variables (IV) algorithm cast into a GMM framework to determine time-varying alpha and beta estimates. They find the only factor to matter in the dynamic GMM approach is the market risk premium. Moreover, Racicot, Rentz, Tessier & Thoret (2019) suggest the traditional static approach of the FF model may be misspecified. They focus on the time-varying nature of the Jensen performance measure $\alpha$ and the market systematic risk sensitivity $\beta$, as these parameters are essentially universal in asset pricing models. Choudhry et al. (2010) find

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that the beta of CAPM is time-varying within Asian crisis in 1997-98 and the post-crisis period. They show that the positive effect of conditional volatility on the time-varying betas in Indonesia, Singapore, South Korea and Taiwan stock markets during the crisis period. Therefore, this research fills the gap by using a GMM framework to study the stock markets during the Covid-19 pandemic, which caused unprecedented economic and financial disruptions across the globe.

2. Data

We aim to test the model in Fama & French (2017), thus we select 10 stocks from their data for the growth portfolio from January 1990 till March 2020. The study applies monthly basis, due to the fact that monthly returns and FF factors are mostly used in literature. The second data uses 6 value-weight portfolios based on size and book-to-market, 6 value-weight portfolios based on size and investment and 6 value-weight portfolios based on size and operating profitability also on monthly basis.

3. The Model

This section introduces Five-factor Fama-French model and the recursive/rolling robust IV algorithm in a GMM framework to estimate time-varying alpha and beta.

3.1. Five-factor Fama-French model

This section follows Racicot, Rentz, Tessier & Théoret (2019) to discuss state space representations of our model. The Fama-French five-factor model introduced by Fama & French (2016) is

\[ r_{i} - r_{f} = \alpha_i + \beta_{\text{mb}}(r_{\text{mkt}} - r_{f}) + \beta_{\text{SMB}} r_{\text{SMB}} + \beta_{\text{HML}} r_{\text{HML}} + \beta_{\text{RMW}} r_{\text{RMW}} + \beta_{\text{CMA}} r_{\text{CMA}} + \epsilon_i \]

where \( r_{i} \) is the total return of individual stocks or portfolio \( i \). \( r_{f} \) represents the risk free asset return. \( r_{\text{mkt}} - r_{f} \) states an expected excess return of individual stocks \( i \). \( \alpha_i \) denotes the constant of the model. \( \beta_{\text{mb}} \) is a beta factor of market risk free rate sensitivity of the rate of return of the \( i \) investment in relation to the market. \( r_{\text{mkt}} \) is the total market portfolio return. \( r_{\text{SMB}} \) describes the excess return on market portfolio index. \( \beta_{\text{SMB}} \) is the beta factor for size of the company, and \( r_{\text{SMB}} \) represents the size premium. \( \beta_{\text{HML}} \) denotes the beta factor for book-to-market value, and \( r_{\text{HML}} \) is the book-to-market premium. \( \beta_{\text{RMW}} \) is the beta factor for profitability, and \( r_{\text{RMW}} \) denotes the profitability premium. \( \beta_{\text{CMA}} \) is the beta factor for investment value, and \( r_{\text{CMA}} \) represents the investment premium. \( \epsilon_i \) is the random error component. Now we turn our attention to explain how the factors are calculated by Fama and French. The five-factor model uses 6 value-weight portfolios depending on size and book-to-market, size and operating profitability, and size and investment.

3.2. GMM models

In line with Racicot, Rentz, Kahl & Mesly (2019), the model in Section 3.1 is potentially measured with errors since it uses what might be viewed as generated regressors and proxies as explanatory variables, and these are known to cause the standard OLS to be biased. Below, we propose a robust IV algorithm that we cast into a recursive/rolling GMM framework for the FF five-factor model. The recursive GMM formulation of our robust instrumental variable estimator is as follows:

\[ \min_{\beta} \left\{ n^{-1} \left[ d_i^\top (Y_i - X_i \hat{\beta}) \right] W_i n^{-1} \left[ d_i^\top (Y_i - X_i \hat{\beta}) \right] \right\} \]

(2)

where \( W_i \) is a weighting matrix that can be estimated using the HAC$^3$ estimator. We define the variables in (2) through (3) to (5). \( Y_i \) is as follows:

\[ Y_i = X_i \beta_i + \epsilon_i \]

(3)

where we assume that \( X_i \) is an unobserved matrix of explanatory variables at time \( t \). Note that a matrix of variables at time \( t \) includes observations from 60-time periods in our rolling version of the regression. We assume that observed matrix of observed variables is to be measured with normally distributed error:

\[ \hat{\beta}_i = \hat{\beta}_{i,\text{TLS}} = (X_i^\top P_{\hat{\alpha}} X_i)^{-1} X_i^\top P_{\hat{\alpha}} Y_i \]

(4)

We define \( P_{\hat{\alpha}} \) is the standard “predicted value maker” or “projection matrix” and use it to compute

\[ P_{\hat{\alpha}} X_i = Z_i (Z_i^\top Z_i)^{-1} Z_i^\top X_i = Z_i \hat{\theta}_i = \tilde{X}_i \]

(5)

where \( Z_i \) is optimally combining the Durbin (1954) and Pal (1980) estimators using GLS. The result is based on the Bayesian approach of Theil & Goldberger (1961). This leads to estimators that are more asymptotically efficient. This approach for obtaining \( Z_i \) is explained in Racicot, Rentz, Kahl & Mesly (2019).

1HAC is the heteroscedasticity and autocorrelation consistent estimator. We used the “Iterate to Convergence” in Newey & West.
4. Empirical results

4.1. The result of the rolling $R^2$

Figure 1 shows the unique $R^2$ of the FF5F model. We demonstrate the impact of selected events, the Dotcom bubble in 1999-2002, the 2007-2010 Financial crisis, the 2009-2013 Debt crisis, and the Covid-19 pandemic crisis from December 2019 to March 2020.

The $R^2$ in growth portfolio has the highest mean with value of 82.99%. The minimal value of $R^2$, 41.94%, is observed on 30.10.1995. The highest $R^2$ of the model is observed on 31.12.2019 with a value of 99.02%. This implies that adding the two additional factors of profitability and investment helps to improve the explanatory power of the model.

Figure 1 shows the following findings. The Dotcom bubble has no influence on the volatility of $R^2$ by a large margin in comparison to the next crises. The mean during this period is 88.62%. The $R^2$ in five-factor model firstly rises from 86.96% in January 2000 to 96.86% in July 2000. It then declines to 81.23% in December 2000. After five months, $R^2$ of the model returns to the high level of 95.16% in February 2001, and it then falls again to 81.72% in a one year period.

The Financial crisis is the only selected crisis that has positive impact on $R^2$ of model. $R^2$ rises from 55.35% in July 2007 to 94.83% in June 2008. The mean of $R^2$ during the financial crisis is 84.39%, which is below the average mean of the portfolio. These results find that adding the two new factors to the model has a significant influence on $R^2$. Moreover, these two factors show a strong importance in lifting the $R^2$ of the model even higher.

The $R^2$ rapidly decreases during the Debt crisis. The mean value of $R^2$ during the Debt crisis is 82.23% which is the lowest of all five events. $R^2$ drops from the original value of 94.05% in March 2012 to 58.99% in April 2013.

The $R^2$ of the model during the Covid-19 outbreak behaves similarly as during the Debt crisis. At the beginning of the event, $R^2$ has value of 99.02% in December 2019. In a three months period, $R^2$ declines to 87.01% in March 2020.

4.2. The rolling beta coefficients of OLS

This section examines the changes of beta coefficients over time. We investigate the changes in their behavior during the selected events with an added 18 months period prior. We determine if the rolling beta coefficients of models can be used as signal indicators for uneventful events that could happen on the US stock markets in the future. The rolling window of model in this part of paper is set to one year. Figure 2 shows the selected events after adding the 18 month period.

The Dotcom bubble increases in 18 months prior period. The biggest spike is observable for HML factor $\beta$ which rises from -1.96 on 31.5.1998 to 0.39 on 31.3.2003. We find that all five factor betas decline before the Financial crisis. During this event, we see a significant difference between beta values of market premium factor and other four factors. The MKT_RF beta has the mean value of 0.91 in 18 months prior period, while other factors experience negative beta values.

The two added factors $\beta$ decrease during the 18 month period. These results suggest that, before the Financial crisis, the profitability of companies in portfolios drops. Moreover, the investment strategy moves from aggressive to more conservative.

All five betas decrease in the Debt crisis during an 18 months prior period, especially the RMW factor $\beta$ declines from 1.34 to -1.43.

Figure 1. The impacts of selected events on $R^2$
in 9 months period. In contrast, the CMA factor $\beta$ increases at the beginning of the prior period from value of -1.96 to 0.11, but then it drops. This indicates that, before the Debt crisis, the difference between the returns of firms who invest conservatively, and those who invest aggressively has significantly decreased.

There are decreases of all five factors in 18 months before the Covid-19 outbreak. This is an interesting results due to the fact that Covid-19 outbreak happens relatively fast. In addition, before this event, the market has achieved historical maxima. The results shown in Figure 2 suggest that with exception of Dotcom bubble, all five factor betas tend to decrease in an 18 months prior period.

4.3. Estimation

This section first presents the descriptive statistics of OLS and rolling/recursive GMM. We then compare the basic estimation of OLS and (Fama & French 2016) with our proposed RIV GMM algorithm (Tables 1 and 2). As explained in Diebold & Yılmaz (2014), a linear model with time-varying parameters like the one that we are estimating in this article is in fact a very general nonlinear model. This follows White’s theorem cited in Granger (2008).

Table 1 provides the descriptive statistics for the monthly excess returns of each of the Fama-French portfolios from January 1999 to March 2020. The mean return is close to 0.3% in our sample, albeit with some minor variation across portfolios. The average standard deviation is somewhat over 7% with positive skewness and kurtosis well above 3. The average Jarque-Bera (JB) statistic is well-above the 1% level of 9.21, ranging from a low of 56.848 for $\beta_{\text{MKT}}$ to a high of 1855.7 for $\beta_{\text{RMW}}$. Most portfolios show first-order serial correlation. The estimator that we propose in this article is based on cross-sample higher moments. Therefore, the fact that there is substantial kurtosis might be seen as another argument in favor of our robust instruments. In addition, because we transpose our instruments into a GMM setting, all the aforementioned nonspherical issues should be addressed (Racicot, Rentz, Tessier & Théoret 2019).

Table 2 displays the descriptive statistics for the factors used in our conditional model. The range of these JB statistics is somewhat smaller than the range in OLS for the portfolio returns, from a low of 10.688 for $\beta_{\text{CMA}}$ to a high of 56.501 for $\beta_{\text{MKT}}$. The small JB values indicates that error are normally distributed. This finding is consistent with Racicot, Rentz, Kahl & Mesly (2019). Nevertheless, all of

| Table 1 |

| Recursive OLS regression estimates |
|-----------------------------------|
| OLS | Mean | Median | Max | Min | Std | Skewness | Kurtosis | JB-test |
|-----|------|--------|-----|-----|-----|----------|----------|---------|
| $\alpha$ | 0.0106 | 0.016 | 0.0003 | 0.0065 | 0.0016 | 3.2926 | 0.1925 | 3.5268 |
| $\beta_{\text{MKT}}$ | 0.006 | 0.011 | -0.1723 | 0.1135 | 0.0423 | 0.7231 | 4.2952 | 56.848 |
| $\beta_{\text{SMB}}$ | 0.001 | 0.0007 | -0.1491 | 0.1832 | 0.0557 | 0.4227 | 7.5416 | 321.89 |
| $\beta_{\text{HML}}$ | 0.0006 | -0.0012 | -0.1412 | 0.1287 | 0.0695 | 0.0176 | 5.925 | 129.11 |
| $\beta_{\text{RMW}}$ | 0.0033 | 0.0037 | -0.1834 | 0.1333 | 0.0755 | 0.4048 | 14.062 | 1855.7 |
| $\beta_{\text{CMA}}$ | 0.0018 | -0.0002 | -0.0686 | 0.0956 | 0.1043 | 0.5999 | 5.2516 | 98.18 |

Notes: The significant level of $\alpha$ are at almost 20%.
these JB statistics have high p-values, leading to a rejection of the null hypothesis of normality. Now we turn our attention to the recursive GMM regression estimates. Table 3 provides the coefficients of all variables to explain the excess returns of portfolio with the biggest magnitude.

The α of portfolio has a coefficient of 0.003, which suggests that this portfolio returns is better than the market risk free rate. The MKT_RF factor has the biggest estimator of 1.069 per month showing that the market risk premium of growth companies are higher than the risk free market rate. The added factors, CMA and RMW, have a mixed impact on returns. CMA factor has the biggest negative coefficient of all variables, -0.20, suggesting that the aggressive investment strategy of companies does not bring bigger returns. The RMW factor with a coefficient of 0.27 implies that the profitability of companies in the portfolio correlates with excess returns of the selected portfolio. The results also indicate that RMW and CMA partially absorb the effects of other factors. MKT_RF and RMW factors are two statistically significant factors in the model. Other three factors tend to be statistically insignificant in explaining the excess returns of the selected portfolio. The F-statistics shows that the model is statistically significant.

Below, Table 4 displays the estimation results.

We find that all of the beta model parameters are insignificant. The GMM estimation may be seen as an alternative to Kalman filtering to obtain time-varying parameters for the performance measure alpha and the systematic risk measure beta (Racicot, Rentz, Kahl & Mesly 2019). Note that \( R^2 \) is -5.963, because \( R^2 \) is no longer bounded between 0 and 1 in the GMM estimation. Moreover, Ghysels (1998) suggests that this modeling approach may lead to biased estimation and a simple static approach may be preferable.

Note that Covid-19 is an extreme event that is well modelled by our designed robust IV GMM which is based on higher cross-sample moments of third and fourth degrees. Taleb (1997) demonstrates that the departure from normality can be properly reflected in these higher moments. However, this tracking of the business cycle is an unintended consequence of our design to account for endogeneity issues and/or measurement errors. Racicot, Rentz, Tessier & Théoret (2019) suggests that these instruments even more appealing to the empirical practitioner. Damodaran (2009) argues that the well-known small-cap anomaly measured via the FF SMB factor might well be primarily a January effect. This justification might explain the insignificance of our GMM estimation. Perhaps the empirical evidence that Damodaran finds could explain why the other factors are insignificant (Racicot, Rentz, Kahl & Mesly 2019). Nonetheless, we believe Fama & French (2017) made a significant contribution by developing a theoretical framework that captures the salient features of expected returns.

5. Conclusion

This study dedicates to show the ability of Fama-French model to explain the monthly excess returns in selected events. The parameter for testing the ability of the model is \( R^2 \) coefficient which rolls over time with a window containing 12 months of data.

We find that the five-factor models retain the \( R^2 \) coefficient which rolls over time with a window containing 12 months of data. Therefore, these results serve only for demonstration, and further study needs to be done to calculate the ultimate impact of this event.

**Notes:** The significant level of α are at almost 20%, based on Newey & West (1987) autocorrelation and heteroskedasticity robust variance-covariance matrix. The GMM estimator is computed according to equation (5).

**Table 2**

|         | Mean   | Median | Max   | Min   | Std    | Skewness | Kurtosis | JB-test |
|---------|--------|--------|-------|-------|--------|----------|----------|----------|
| \( \alpha \) | -0.0043 | 0.0031 | 0.0027 | 0.0113 | 1.6104e-03 | 0.0503 | 2.3053 | 6.2205 |
| \( \beta_{MKT} \) | 1.0261 | 1.0507 | 0.6952 | 1.2564 | 4.2669e-02 | 0.9327 | 3.997 | 56.501 |
| \( \beta_{SMB} \) | -0.0009 | -0.0085 | -0.532 | 0.5559 | 7.4538e-02 | 0.42987 | 2.9969 | 9.3319 |
| \( \beta_{HML} \) | 0.00053 | 0.0352 | -0.377 | 0.2994 | 8.8572e-02 | 0.4528 | 2.1593 | 19.279 |
| \( \beta_{RMW} \) | 0.228 | 0.186 | -0.311 | 0.719 | 1.3364e-01 | 0.15083 | 2.112 | 11.10 |
| \( \beta_{CMA} \) | -0.230 | -0.199 | -0.922 | 0.297 | 9.1965e-02 | 0.3316 | 2.362 | 10.688 |

5. Conclusion

This study dedicates to show the ability of Fama-French model to explain the monthly excess returns in selected events. The parameter for testing the ability of the model is \( R^2 \) coefficient which rolls over time with a window containing 12 months of data.

We find that the five-factor models retain the \( R^2 \) value on a high enough level to consider them as statistically significant. There is only one \( R^2 \) of five-factor model rises during the Covid-19 outbreak and experiences the highest level of \( R^2 \) during the observable period.

The influence of Dotcom bubble to the \( R^2 \) of growth model is statistically significant. The \( R^2 \) of growth portfolios decreases rapidly during the Financial crisis of 2008. The Covid-19 outbreak has led to a substantial drop in the \( R^2 \) during this event.

The descriptive statistics displays that the Jarque–Bera statistics of GMM is smaller than the ones in OLS. The estimation of OLS finds that only market risk-free rate and the profitability matters to OLS. However, all of the beta model parameters are insignificant in the GMM regression.

It is necessary to mention that the Covid-19 outbreak event is differs from other selected events, in that this outbreak is still ongoing. The reason for choosing this event is that this paper examines the results of rolled \( R^2 \) beta coefficients in Covid-19. Therefore these results serve only for demonstration, and further study needs to be done to calculate the ultimate impact of this event.

**AUTHORSHIP STATEMENT**

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All persons who meet authorship criteria are listed as authors, and all authors certify that they have participated sufficiently in the work to take public responsibility for the content, including participation in the concept, design, analysis, writing, or revision of the manuscript. Furthermore, each author certifies that this material or similar material has not been and will not be submitted to or
Table 3
The estimators of OLS

| Explanatory variable | Coefficient | STD.E | P value | T value | PR(>|T|) |
|----------------------|-------------|-------|---------|---------|----------|
| α                    | 0.0034      | 0.0016| 0.032   | 2.159   | 0.0315*  |
| MKT_RF               | 1.0692      | 0.0422| 0.0000  | 25.3400 | < e-16*** |
| SMB                  | 0.0009      | 0.0557| 0.9880  | 0.0160  | 0.9875   |
| HML                  | -0.0728     | 0.0695| 0.2960  | -1.0470 | 0.2957   |
| CMA                  | -0.2005     | 0.1043| 0.0550  | -1.9220 | 0.0554   |
| RMW                  | 0.2757      | 0.0755| 0.0000  | 3.6500  | 0.0003   |
| Residuals            | -0.0913     | -0.0176| 0.0001  | 0.0167  | 0.1172   |

Notes: ***, **, *, respectively, significant at 1%, 5%, and 10%. T value is the ratio of the departure of the estimated value of a parameter from its hypothesized value to its standard error. PR(>|T|) is the probability of observing any value larger than T. The results of F test give 182.4 with degree of freedoms are 5 and 356, which provides the p values is less than 2.2e-16.

Table 4
The estimators of GMM

| Explanatory variable | Coefficient | STD.E | z value | PR(>|z|) |
|----------------------|-------------|-------|---------|---------|
| α                    | -0.0042     | 0.1018| -0.041  | 0.967   |
| MKT_RF               | 0.0115      | 0.1237| 0.0093  | 0.926   |
| SMB                  | -0.011      | 0.0691| -0.16   | 0.873   |
| HML                  | -0.0159     | 0.1052| -0.152  | 0.88    |
| CMA                  | 0.0247      | 0.1244| 0.198   | 0.843   |
| RMW                  | 0.0005      | 0.0275| 0.128   | 0.898   |
| Residuals            | -0.0141     | -0.0072| -0.0022 | 0.0267  | Max      |

Notes: z value is the ratio of the departure of the estimated value of a parameter from its hypothesized value to its standard error. PR(>|z|) is the probability of observing any value larger than z. Note that the R2 is no longer bounded between 0 and 1.

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Authorship contributions

Please indicate the specific contributions made by each author (list the authors' initials followed by their surnames, e.g. D. Horváth and Y.-L. Wang). The name of each author must appear at least once in each of the three categories below.

Category 1
Conception and design of study: D. Horváth, Y.-L. Wang; acquisition of data: D. Horváth, Y.-L. Wang; analysis and/or interpretation of data: D. Horváth, Y.-L. Wang.

Category 2
Drafting the manuscript: D. Horváth, Y.-L. Wang; revising the manuscript critically for important intellectual content: D. Horváth, Y.-L. Wang.

Category 3
Approval of the version of the manuscript to be published (the names of all authors must be listed): D. Horváth, Y.-L. Wang.

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Appendix A List of growth stocks

Advanced Micro Devices (NYSE: AMD) is an American hardware company operating worldwide and was founded on May 1, 1969 in California. The company focuses on the development of processors, microprocessors, and chipsets and supplies it to third-party foundries. AMD serves customers worldwide.

Apple Inc. (NYSE: AAPL) is an American technology company founded in 1976 in Silicon Valley, California. The company's main program is the production and development of personal computers and their software, the production and development of iPhone smartphones, iPads and more. Apple is the world's largest technology company by revenue and one is the first company in the world the market capitalization of which rose to one trillion US dollars.

Charles Schwab Corporation (NYSE: SCHW) is an American multinational company founded and based in San Francisco, California
which focuses on providing a variety of financial services for customers. The firm also provides securities brokerage, banking and other financial services in the United States.

FedEx Corporation (NYSE: FDX) is a global US courier and logistics company based in Memphis, Tennessee. FedEx, formerly FDX Corporation, is an American courier and logistics company founded in 1971. The name is an acronym to the name of the original Federal Express division.

Hershey Company (NYSE: HSY) is an American multinational company which manufactures chocolate and sugar products. Main products include chocolate and sugar based products, gum and pantry items, such as baking ingredients, toppings, and beverages. Hershey Company is operating across 60 countries worldwide.

Microsoft Corporation (NYSE: MSFT) is an American multinational corporation based in Redmond, Washington and established on 4 April 1975. The company deals with the development, production, licensing and support of a wide range of products and services that are primarily related to computers. Microsoft also develops music entertainment devices and game consoles.

Nike Inc. (NYSE: NKE) is an internationally sporting goods manufacturer founded in 1964 and based in Beaverton, Oregon. The company focuses on designing and developing athletic footwear and apparel. Nike Company is selling the products through its own stores, subsidiaries, and distributors worldwide.

Procter & Gamble Company (NYSE: PG) is an American multinational concern primarily active in the field of drugstore goods. The company provides products mainly for laundering and cleaning, also for beauty care that are selling primarily through the chains of grocery stores and drug stores.

Walt Disney Company (NYSE: DIS) is an American media and entertainment company. The main business is the production of animated films and entertainment films. The company employs more than 223000 employees who are providing park experiences, consumer products, studio entertainment, networks and channels on TV.

Walmart Inc. (NYSE: WMT) is an American company which is operating a chain of large discount department stores. The Company offers a variety of products and it is known as one of the biggest consumer staples sector companies with 2 million employees.

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