# Empirical project - Excess returns

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## 1 Introduction

As soon as the beginning of the sixties, several economists such as William Sharpe developed what is nowadays known as portfolio theory. One of the main goal was to determine the optimal return of an asset that would compensate the risk-taking of an investor when buying some stock. It was then proven that specific risk, which is related to a specific firm, faded away with diversification of a portfolio. However diversification is not enough to alleviate systematic risk, which is a risk related to general market moves, such as inflation for instance. Consequently, the Capital Asset Pricing Model (CAPM) of Sharpe [1964] and Lintner [1965] was designed in order to determine the 'fair price' of an asset or a portfolio, the price that would make up for systematic risk. This single-period model provides a simple relationship between the expected return of the security and the market risk of the security. But empirical evidence points out the flaws of the traditional CAPM model. It indeed takes into account only one source of systematic risk, namely the market risk. In fact, soon after its design, Ross [1976] and his Arbitrage Pricing Theory (APT) challenged the single-factor model by allowing several other risk factors in the asset pricing model. This is the starting point of a thriving field of research in order to identify variables of interest, both macro-economic and firm-related. For instance, He [2002] suggests that a real estate factor can be used to explain excess returns on industrial stocks.

Our work falls within the ATP approach of determining whether other risk factors can explain excess returns. We will use as dependent variable the excess returns on the FTSE small cap index, which is a portfolio of the small market capitalisation companies including the 351st to the 619th largest companies of the London Stock Exchange main market. We will consider as potential risk factors some macro-economic time series, such as the monthly inflation rate for instance.

After a brief overview of the literature regarding this topic in Section 2, Section 3 presents in greater details both CAPM and the ATP model. In Section 4, we describe our data and how each variable is constructed. The econometric methodology is presented in Section 5 while Section 6 reports and comments our empirical results. Finally, Section 7 concludes.

## 2 Litterature review

Barely several years after the design of the CAPM in the mid 60s by Sharpe [1964] and Lintner [1965] seminal papers, the existence of other risk factors than the market risk was investigated to explain excess returns.

First, some studies reveal the importance of some firm-related characteristics. Basu [1977] shows that a firm's Price-Earnings ratios can contribute to excess returns. In the same line, Ball [1978] claims that not adding firms' earnings in the CAPM might result in an omitted variable bias. Banz [1981] brings to light the importance of the so-called ‘size effect’ : the difference in risk-adjusted returns according to a company’s size, although the author admits not knowing whether this size variable is actually a proxy for some unobserved factor(s). Beside, Stattman [1980] and Rosenberg, Reid and Lanstein [1985] find a positive relation between the US stock market’s average returns and its book-to-market ratio. Fama and French [1993] go even further by designing their own three-factor model keeping market risk as explanatory variable but adding two other variables : the company size, and the company price-to-book ratio.

Other studies point to more macro-economic risk factors. Among others, Chen, Roll and Ross [1985] find several variables of interest such as unexpected changes in inflation rate and unexpected changes in the yield curve. It is also worth mentioning the role of real estate factor on excess returns of industrial stocks exhibited by He [2002] along with other variables. Another important contribution to this empirical literature can be found in Keim [1983] which gives evidence of the existence of a so-called ‘January effect’, namely the increase of stock excess returns in January. Those numerous studies all point out anomalies in the Capital Asset Pricing Model as designed by Lintner [1965] and Sharpe [1964] by finding several risk factors to explain excess returns of a stock portfolio.[1]

## 3 Theoretical framework

Let us describe more precisely the two competing theories at hand. The Capital Asset Pricing Model was first introduced by Lintner [1965] and Sharpe [1964] based on the previous work of Harry Markowitz. It provides a simple formula to compute

[1]See the survey by Fama and French [2004] and the references therein.

the optimal rate of return of a security or a portfolio. Its main underlying assumptions are that *i)* all investors are single period risk-averse and final wealth utility maximizers, *ii)* the portfolio choices rely on mean and variance criteria only, *iii)* there are no taxes nor transactions costs, *iv)* all investors have homogeneous views regarding the parameters of the joint probability distribution of all security returns, *v)* they all can borrow and lend at a given risk-less rate of interest. It establishes the following relation between the expected excess return of an asset and the expected excess return on the 'Market porfolio' :

$$\mathbb{E}[R_i] - R_f = \beta_i(\mathbb{E}[R_m] - R_f)$$

Hence, the model has the following regression form :

$$R_{i,t} - R_{f,t} = \alpha_i + \beta_i(R_{m,t} - R_{f,t}) + \varepsilon_{i,t},$$

where :

- $R_{i,t}$ is the return of asset i at time t

- $R_{f,t}$ is the return on the risk-free asset at time t

- $R_{m,t}$ is the return on the market portfolio at time t

- $\varepsilon_{i,t}$ is a white noise i.e serially uncorrelated, zero-mean and constant variance process

- $\alpha_i$ is a constant term introduced to allow for a systematic pricing error.

This simple model is used to determine the optimal return of a portfolio taking into account only the market risk. For example, if $\beta_i$ (also called market $\beta$) is found to be positive, then the portfolio is said to be sensitive to market risk. Hence, the investor gets a compensation also called risk premium since $R_{i,t} > R_{f,t}$.

The simplicity of this model might also be one of its main drawback. Indeed, one could consider other relevant risk factors that could lead to an omitted variable bias if they were to be forgotten. The estimator of $\beta_i$ would then be biased. As mentioned previously, lots of studies provide statistical evidence that some common risk factors might indeed be omitted.

Another criticism made to this model is that the market portfolio cannot be observed directly and is therefore usually approximated by a proxy variable like S&P 500 or FTSE 100 for instance. This is also known as 'Roll's critique'[2].

So as to overcome some of the above criticisms, the Arbitrage Pricing Theory (APT) proposes a generalisation of the CAPM to a multi-factor model given by

$$R_{i,t} - R_{f,t} = \alpha_i + \beta_{i,1} F_{1,t} + \beta_{i,2} F_{2,t} + ... + \varepsilon_{i,t}$$

where all $F_{k,t}$ represent a systematic risk.

One problem of APT is that it allows to use infinitely many $F_{k,t}$. Hence, one could be tempted to do so in order to increase the value of the coefficient of determination, leading to over-fitting problems. However, one advantage of this model is that the CAPM appears as a particular case of it, in which all the coefficients associated to factors other than the market risk are equal to zero.[3] The various factors which will be considered in our empirical analysis are carefully described in the next section.

[2] See Roll [1977].

[3] As such, the CAPM can be tested formally from the APT regression using a joint hypothesis test such as the Wald test for instance.

# 4 Data description

Most of the series used for the subsequent empirical analysis come from Datastream. These are monthly data from December 1993 to January 2017, which is the longest available span of time covered by all the series required for our study[4].

First, the dependent variable is the excess returns on small market capitalisation companies (small caps hereafter) and is denoted $xr_{ftse-sc}$. It is defined as the difference between the monthly rate of return (dividends included) of the "Financial Times Stock Exchange"[5] small caps and a monthly risk free rate of return. The monthly rate of return of the footsie small caps, denoted $r_{ftse-sc}$, is calculated as the monthly growth rate ($\times$ 100) of the FTSE small caps total return index called FTSESCO(RI) in Datastream. Regarding the risk free rate, we follow the most widespread use in this empirical literature by retaining the UK three-month Treasury bill tender. More precisely, the (annualized) rate of return given by the series called UKTBTND(IR) in Datastream is used to calculate the monthly three-month rate of return (denoted tb3m from now on) as follows:

$$tb3m = \left( \left( 1 + \frac{UKTBTND(IR)}{100} \right)^{(1/12)} - 1 \right) \times 100.$$

It is worth noticing that the series UKTBTND(IR) corresponds to the rate collected at the beginning of each month while all other series correspond to end-of-month values. To solve this problem, the series UKTBTND(IR) has been lagged by one month: for instance, the value corresponding to the beginning of February is assigned

[4] Actually, the 10-year government securities yield series which is not available in Datastream was found on the Bank of England website. Unfortunately, the Bank of England data set is available since December 1993 only.

[5] We will refer to it by its initials FTSE or by its informal name "footsie".

to end of January instead. Therefore, the available sample will end in December 2016 instead of January 2017. Finally, the excess return on small caps is defined as:

$$xr_{ftse-sc} = r_{ftse-sc} - tb3m.$$

Regarding the explanatory factors, the market return considered in the CAPM approach is measured here by the FTSE100 rate of return (dividends included). Indeed, the FTSE100 index corresponds to the one hundred most highly capitalised UK companies listed on the London Stock Exchange. This return, denoted $r_{ftse100}$, is computed from the growth rate of the FTSE100 total return index series called FTSE100(RI) in Datastream base. So as to test the Arbitrage Pricing Theory model, the following factors are also considered:

- Dum1: A dummy variable which takes on value 1 in January and 0 for all other months.
- FTSE100DY: The FTSE100 dividend yield (FTSE100(DY), Datastream).
- BRENT: The crude oil dated Brent price in US$/BBL (OILBRDT(P), Datastream).
- INFLA: The UK Consumer Price Index annual percentage change - All items (UCPANNL, Datastream).
- IPI: The UK index of industrial production - All production industries (UKIPTOT.G, Datastream).
- M0: The UK narrow money supply, consisting in the notes and coins in circulation outside Bank of England (UKM0B, Datastream).

- SPREAD: The difference between the annualized UK nominal yield from British 10-year government securities (called IUMAMNPY in the Bank of England data base) and the annualized rate of return of the 3-month Treasury bills given by the series called UKTBTND(IR) in Datastream.

- $xr_{ftse100}$: The excess return on FTSE100, defined as $r_{ftse100} - tb3m$.[6]

All these series are seasonally adjusted when required. They are plotted in the Appendix, Figure 1.[7] As can be seen from these graphs, the (excess) return series look very different from the other ones, in that they look much less persistent. Table 2 shows that their standard deviation (compared to their mean) is actually very high. When computing their coefficient of variation (standard deviation divided by the mean), it turns out that the ones of the two excess return series are slightly greater than ten, while the ones of the dividend yields, Brent price, consumer price index or industrial production index are lower than one. A closer look also reveals that the excess returns on small caps have a larger mean and variance than the excess return on FTSE100. The last four raws of Table 2 refer to Skewness and Kurtosis coefficients of each series. If they were Gaussian distributed, then their skewness should be zero and their kurtosis should be three. This is the joint assumption tested by the Jarque-Bera statistics given in the last rows of Table 2. Under the null of normality, this statistics should be zero. The last raw of this table shows the probability of this null to be true. It can be seen that it is strongly rejected for all the series but the dividend yield.

[6]Due to collinearity issues, the spread between small caps and FTSE100 returns cannot be included among regressors along with $xr_{ftse100}$.

[7]Table 2 in Appendix reports their summary statistics.

# 5 Econometric models and estimation methods

To be able to determine risk factors for excess returns, we will use a multi-factor model approach. We will regress our dependent variable $xr_{ftse-sc}$, the excess returns of the FTSE small caps portfolio, on a proxy for the market portfolio as suggested by CAPM and other regressors as suggested by the ATP model.

However, some series such as the money supply or the Brent price look much more persistent than the return series. So as to avoid the introduction of non-stationary regressors in the regression, Augmented Dickey-Fuller (ADF) unit root tests are first performed.[8] Let us denote $y_t$ a time series for which one wants to test the null hypothesis of unit root (or non-stationarity). The ADF test relies on the following auxiliary regression:

$$\Delta y_t = \rho y_{t-1} + \sum_{i=1}^{k} \Delta y_{t-i} + u_t, \tag{1}$$

where $u_t$ is a zero-mean, not serially correlated white noise process with constant variance. The unit root null hypothesis corresponds to:

$$H_0 : \rho = 0,$$

in which case $y_t$ follows a random walk. The autoregressive lags, $\sum_{i=1}^{k} \Delta y_{t-i}$, are introduced in the regression so to eliminate serial correlation in the $u_t$ process, if any.[9] Hence, the number of lags $k$ will be chosen as the smallest one which makes the $u_t$ not serially correlated.[10] Dickey and Fuller have shown that the distribution of their test statistics depends on the deterministic component which may be

[8] See Dickey and Fuller [1979] and Dickey and Fuller [1981].

[9] As will be seen below, some series do not require the introduction of any autoregressive lags, in which case the test shrinks to the more simple Dickey-Fuller (DF) test.

[10] To this end, the Breusch-Godfrey test for no serial correlation — which is described below — is applied to the estimated residuals of the (A)DF auxiliary regression.

required in Equation (1). Actually, in Equation (1) above where no intercept nor deterministic trend has been introduced, under the stationary alternative ($|\rho| < 1$), $y_t$ would fluctuate around zero. Yet, as can be seen from the graphs in the Appendix, this is seldom the case. For instance the excess return series or the spread series fluctuate around a positive mean. To account for it, Equation (1) has to be modified by including an intercept term. For some other series such as the Brent price of the money supply, the alternative stationary assumption clearly requires the introduction of a deterministic trend as well. In the subsequent analysis, we follow the use in this empirical literature by taking in logarithms all the series which are not already expressed in terms of rates or yields, namely BRENT, IPI and M0. From the ADF tests reported in Table 3 in the Appendix, it turns out that the unit root null hypothesis cannot be rejected for log(BRENT), INFLA, log(IPI) and log(M0), while it is rejected at the 1%-level for all the excess return and return series and at the 10%-level for the FTSE100DY and SPREAD series. Hence, BRENT, IPI and M0 will be taken in growth rates, denoted respectively DBRENT, DIPI and DM0, while the inflation rate will be taken in first difference and denoted DINFLA.[11]

Then, in the line of He [2002]'s analysis for instance, we will study the following general ATP model[12]:

$$xr_{ftse-sc_t} = \alpha + \beta_1 Dum1_t + \beta_2 FTSE100DY_t + \beta_3 DBRENT_t + \beta_4 DINFLA_t + \beta_5 DIPI_t + \beta_6 DM0_t + \beta_7 SPREAD_t + \beta_8 xr_{ftse100_t} + \varepsilon_t, \tag{2}$$

where $\varepsilon_t$ is a zero-mean, not serially correlated white noise process with constant

[11] It can be seen from Table 3 that the unit root null hypothesis is strongly rejected DBRENT, DINFLA, DIPI and DM0.

[12] Unlike He [2002], we do not consider the real estate return as a potential explanatory variable since the relevant series is not available in Datastream.

variance, $\forall t$.

Our methodology will be quite similar to He [2002] as it will consist in running several OLS regressions on different periods of time to assess thoroughly the significance of our potential risk factors. Using the Ordinary Least Squares (OLS) method seems appropriate. However, if some particular conditions are not met, our estimators might be either biased, not consistent or not efficient, the latter leading to inference errors.

In particular, homoskedasticity (i.e $var(\varepsilon_t) = \sigma^2, \forall t$) is required for the estimator $\widehat{\sigma}^2$ to be unbiased. This condition is therefore crucial for the validity of any inference made on the estimators $\widehat{\beta}_i$, $i \in \{1, ..., 8\}$. To test for heteroskedasticity, we use the White-test [13]. This test consists in regressing the estimated squared error terms $\widehat{\varepsilon}^2$ on all the regressors, the square of the regressors and all the cross products.

$$\widehat{\varepsilon}_t^2 = \alpha_0 + \alpha_1 Dum1_t^2 + \alpha_2 FTSE100DY_t^2 + ... + \alpha_9 FTSE100DY_t + ... + \alpha_{17} Dum1_t \times FTSE100DY_t + ... + \alpha_{43} Dum1_t \times xr_{ftse100_t} + u_t.$$

Note that $Dum1_t = Dum1_t^2$ since it is a dummy variable. Therefore, it is not included in the above regression.

We want to test $H_0 : \alpha_1 = ... = \alpha_{43} = 0$ in the equation above. Under the null of homoskedasticity, $T \times R^2 \hookrightarrow \chi^2(43)$ where T is the number of observations. Here $T \times R^2 \hookrightarrow \chi^2(43) = 99.54$ which leads us to reject $H_0$.

As stated previously, we need a valid estimator of $\sigma^2$ to make proper inference on the $\beta_i$'s. Hence, we will use White heteroskedasticity-consistent standard errors and covariance.

[13] See White [1980].

Another essential condition for inference under OLS is the absence of serial correlation. Here we will use the Breusch-Godfrey test[14] for serial correlation for auto regressive processes of order 12. We first estimate the auxiliary regression:

$$\widehat{\varepsilon}_t = \alpha_0 + \alpha_1 Dum1_t + ... + \alpha_8 xr_{ftse100_t} + \rho_1 \widehat{\varepsilon}_{t-1} + ... + \rho_{12} \widehat{\varepsilon}_{t-12} + u_t,$$

from which we want to test $H_0 : \rho_1 = ... = \rho_{12} = 0$. Under this null of no serial correlation, $(T-12) \times R^2 \hookrightarrow \chi^2(12)$. Here $(T-12) \times R^2 = 11,72$ which is far lower than the corresponding 5%-level critical value. Consequently, the null hypothesis of no serial correlation cannot be rejected and is thus accepted.

[14] See Breusch [1978] and Godfrey [1978].

# 6 Empirical results and interpretation

Table 1: $xr_{ftse-sc}$ models estimates

| Model | 1 | 2 | 1.1 | 1.2 | 1.3 |
|---|---|---|---|---|---|
| Sample | 1993m12-2016m12 (whole sample) | | 1993m12-2000m12 | 2001m1-2007m12 | 2008m1-2016m12 |
| $\alpha$ | 1.12 | 3.42 | 5.30* | 1.04 | -1.99 |
| | (1.70) | (2.38) | (2.90) | (3.91) | (5.58) |
| DUM1 | 2.55*** | 1.14 | 3.52** | 3.94*** | 1.18 |
| | (0.70) | (0.92) | (1.39) | (1.14) | (0.89) |
| FTSE100DY | -0.54 | -1.22 | -1.97** | -0.31 | 0.23 |
| | (0.51) | (0.74) | (0.93) | (1.19) | (1.45) |
| DBRENT | 0.04** | 0.08*** | 0.03 | 0.02 | 0.05 |
| | (0.02) | (0.03) | (0.03) | (0.04) | (0.03) |
| DINFLA | -0.56* | -1.06 | 2.30 | -1.03 | -1.19 |
| | (0.92) | (1.38) | (1.73) | (1.94) | (0.97) |
| DIPI | 0.31 | 0.76* | 0.30 | 0.21 | 0.48 |
| | (0.25) | (0.43) | (0.69) | (0.26) | (0.49) |
| DM0 | 0.39 | 0.51 | 0.26 | -1.21 | 1.25 |
| | (0.61) | (0.75) | (0.90) | (1.03) | (0.91) |
| SPREAD | 0.35** | 0.68** | 0.93 | 0.97* | 0.39 |
| | (0.17) | (0.28) | (0.57) | (0.56) | (0.32) |
| $xr_{ftse100}$ | 0.89*** | - | 0.65*** | 1.19*** | 0.93*** |
| | (0.07) | (-) | (0.10) | (0.12) | (0.11) |
| Adj-$R^2$ | 0.57 | 0.07 | 0.44 | 0.63 | 0.64 |

***, ** and * represent respectively the 1%, 5% and 10% significance levels.

The sub-periods studied were chosen in such a way that they all contain a comparable number of observations. Matter-of-factly, these sub-samples allow to study potential differences that could have occured in the aftermath of the 2007 subprime crisis and the subsequent European debt crisis of the early 2010s. Unsurprisingly, the most significant variable for any period is $xr\_ftse100$ as this simply is a proxy for the market portfolio as given by the CAPM model. In fact, removing it from our model (model 2) leads to a dramatic decrease of the adjusted $R^2$ from 0.57 to 0.07. We can now wonder whether adding other factors than the market portfolio is relevant, i.e whether an APT model is appropriate for our data. This question is of interest because although some variables like DUM1 seem to be significant, model 2 emphasises how huge is the amount of variance explained by $xr_{ftse100}$.

To sketch an answer to this question, we test the joint significance of the variables using the Wald test for $H_0 : \beta_1 = \beta_2 = ... = \beta_7 = 0$ in Equation (2). The test statistic follows a $\chi^2(7)$ distribution. Its value, 25.20, is well above the 1% level critical value, 18.48 so we reject $H_0$ at the 1% significance level. Hence it seems that adding other variables is actually relevant.

However, the same test indicates that it is impossible to reject $H_0$ at the 5% confidence level in the third sub-period (model 1.3). This result is easily understandable as no variable but $xr_{ftse100}$ is significant in this last model. This indicates that our result tending to show some superiority of the APT model over the CAPM on our data set must be taken cautiously. It does not seem to be robust when considering different sub-samples.

Among the variables significant on the whole period, the January dummy seems to be the most important given its dimension (2.55) and very low p-value. According to those results, one can observe an increase of excess returns in January compared to the other months. This illustrates the so-called 'January effect' first observed by Rozeff and Kinney [1976] which is a well-known anomaly in the wake of the efficient market hypothesis of Fama and Malkiel [1970]. According to this theory, price always reflects available information and as a consequence, security prices follow a random walk; one cannot predict future prices on publicly available information. You 'cannot beat the market'. Hence, any abnormal excess returns should be explained by luck rather than strategy. However, as shown on the regression table, the January effect is highly significant in two of the three sub-periods and always positive, although such a well-known effect should disappear with time in an efficient market. This oddity was first remarked by Haugen and Jorion [1981], who provided evidence of the persistence of the 'January effect'.

Our result are not surprising as Reinganum [1983] gives evidence that this effect is in fact a small-capitalisation phenomenon. Hence, the importance of January on the FTSE Small-cap index is understandable. However, our results on the last sub-period December 2007 - December 2016 tend to show that the January effect is actually disappearing as its coefficient is not even significant at the 10% significance level.

Another relatively important variable is DBRENT as its coefficient is significant at the 5% significance level. Many researchers, like Casassus and Higuera [2011], provide evidence of the predictive power of oil price changes on excess stock returns in the short run, which might maybe explain the effect of DBRENT, the series of monthly oil price changes. However, our study does not include any lag as its aim is not to find predictors of excess returns but common risk factors. Furthermore, we should be cautious when looking at this coefficient as it is not significant on any of the sub-periods. The same remark can be applied to the variable SPREAD, the interest rate spread, which is rather significant in the full sample model but insignificant on every sub-period. Studies have demonstrated the predictive power of the term spread[15], although to our knowledge, no major study has tried to study its potential contemporary effect on stock excess returns.

[15] See Domian and Reichenstein [1998]

The same remark applies to variable DINFLA which is significant at the 10% level, although not significant in any of the sub-periods. Chen et al. [1985] demonstrated the predictive power of unexpected changes in the inflation rate on expected returns. This might explain the (weak) contemporaneous explanatory power of the above-mentioned variable but once more, we must be cautious.

# 7 Conclusion

In this study, we have explored the explanatory power of various risk factors on UK small cap stock excess returns by estimating different models over different periods of time. Our empirical results tend to show that the multiple factor model (ATP) outperforms the CAPM for the data considered. We have identified several relevant variables, namely the January dummy, the inflation rate, the oil price and the interest rate spread. However only the January effect seems to be robust on most sub-periods and is generally highly significant.[16]

Nevertheless, our conclusions must be tempered as the last sub-period after the 2007 subprime financial crisis fails to reveal any other significant variables than the market risk. Moreover, the latter seems essential to explain the excess returns as can be seen from the drastic drop between model 1 (including market risk factor) and model 2 (excluding market risk factor) adjusted $R^2$s. Consequently, it seems bold to rule out the CAPM for our data, in particular for the last sub-period considered. Finally, our study might also be the subject of Roll's criticism[17]. Indeed, the variable $xr_{ftse100}$ cannot be a perfect proxy for the market portfolio as the latter

[16] As aforementioned, this effect could be expected since it has been shown by Reinganum [1983] to have a strong link with small-cap firms and to be persistent over the years.

[17] See Roll [1977].

is intrinsically unobservable. Hence, although they reveal a few risk factors, our empirical results are to be considered cautiously.

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# 8 Appendix

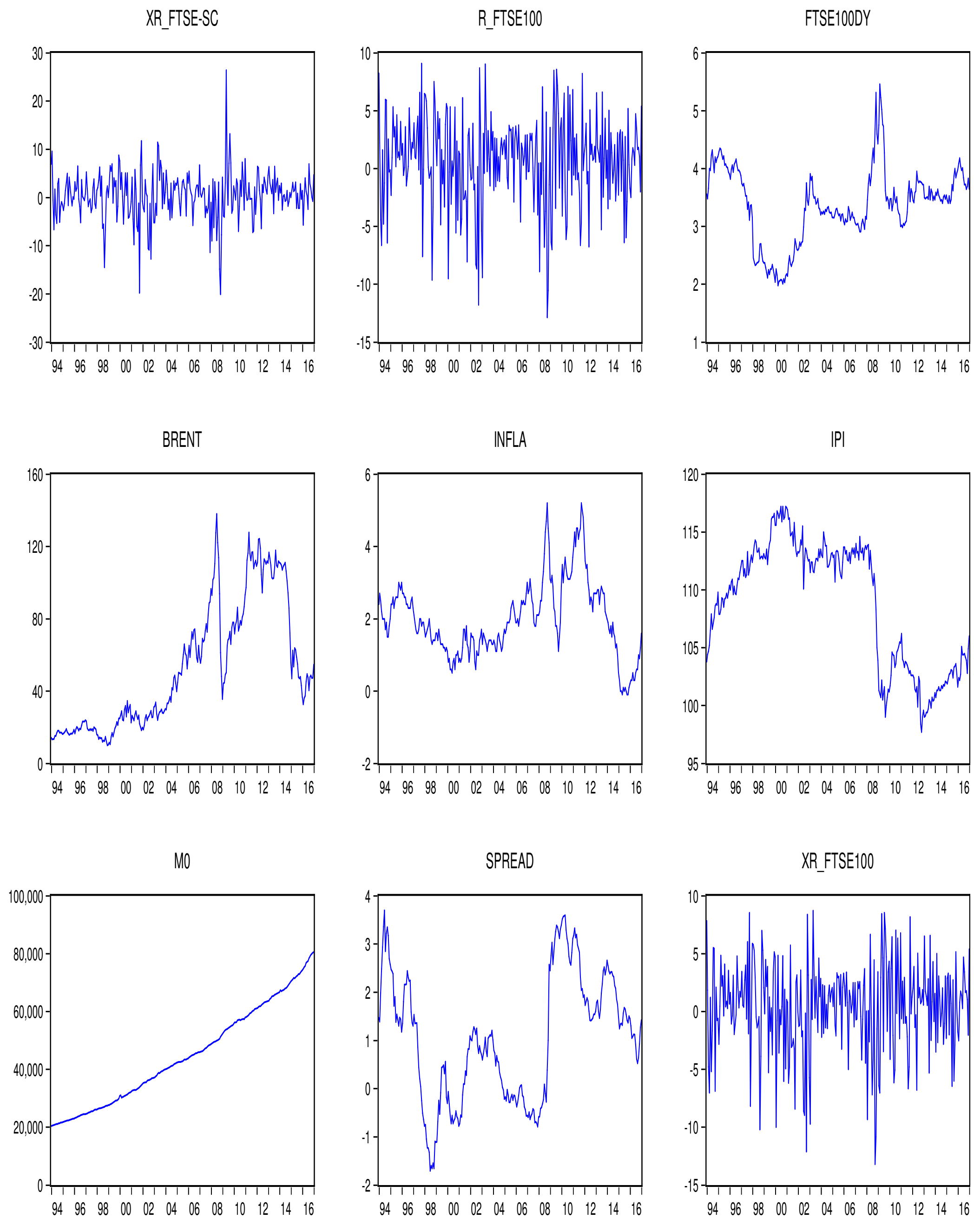


Figure 1: The data

Table 2: Descriptive Statistics (1993m12-2016m12)

| | $xr_{ftse-sc}$ | $r_{ftse100}$ | FTSE100DY | BRENT | INFLA | IPI | M0 | SPREAD | $xr_{ftse100}$ |
|---|---|---|---|---|---|---|---|---|---|
| Mean | 0.447 | 0.664 | 3.372 | 52.57 | 1.987 | 108.8 | 44833.4 | 1.042 | 0.376 |
| Median | 0.773 | 0.960 | 3.450 | 44.23 | 1.900 | 111.0 | 42778.0 | 1.115 | 0.666 |
| Maximum | 26.40 | 9.091 | 5.460 | 138.0 | 5.200 | 117.2 | 80525.0 | 3.696 | 8.722 |
| Minimum | -20.05 | -12.86 | 1.980 | 9.930 | -0.100 | 97.70 | 20449.0 | -1.702 | -13.20 |
| Std. Dev. | 4.880 | 3.962 | 0.653 | 35.14 | 1.050 | 5.407 | 16935.3 | 1.321 | 3.968 |
| Skewness | -0.267 | -0.598 | -0.065 | 0.646 | 0.574 | -0.366 | 0.308 | 0.071 | -0.599 |
| Kurtosis | 7.603 | 3.556 | 3.210 | 2.067 | 3.465 | 1.668 | 1.928 | 2.048 | 3.592 |
| Jarque-Bera | 247.8 | 20.06 | 0.705 | 29.33 | 17.73 | 26.66 | 17.65 | 10.69 | 20.60 |
| Probability | 0.00 | 0.00 | 0.70 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |

Table 3: Augmented Dickey-Fuller Unit Root Tests (1993m12-2016m12)

| Series | Deterministic | Lag order | t-stat | Probability of $H_0$ | Integration order |
|---|---|---|---|---|---|
| $xr_{ftse-sc}$ | C | 0 | -13.02*** | 0.00 | I(0) |
| $r_{ftse100}$ | C | 0 | -16.42*** | 0.00 | I(0) |
| FTSE100DY | C | 4 | -2.53* | 0.10 | I(0) |
| log(BRENT) | C+T | 0 | -1.85 | 0.68 | I(1) |
| DBRENT | C | 0 | -16.47*** | 0.00 | I(0) |
| INFLA | C | 12 | -1.55 | 0.50 | I(1) |
| DINFLA | C | 12 | -6.41*** | 0.00 | I(0) |
| log(IPI) | C | 1 | -1.32 | 0.62 | I(1) |
| DIPI | C | 0 | -19.90*** | 0.00 | I(0) |
| log(M0) | C+T | 2 | -1.36 | 0.87 | I(1) |
| DM0 | C | 1 | -13.04*** | 0.00 | I(0) |
| SPREAD | C | 6 | -2.79* | 0.06 | I(0) |
| $xr_{ftse100}$ | C | 0 | -16.38*** | 0.00 | I(0) |

C: intercept in the ADF regression. C+T: intercept and deterministic trend in the ADF regression. Lag order: number of autoregressive lags (in difference) in the ADF regression, chosen as the smallest one required to eliminate residuals serial correlation. ***, ** and * represent respectively the 1%, 5% and 10% significance levels.