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Pervasive Influences on the US Stock Market Returns

An empirical assessment using panel data analysis

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Abstract

Ross's (1976) theory of Arbitrage Pricing requires news related to the factors affecting stock prices to be mean-zero, serially uncorrelated white-noise processes, though it specifies neither the number nor the identity of these factors. In this study we test whether six candidate factors namely, industrial production growth, inflation, movements of default premium, shifts in the slope of yield curve, policy-related uncertainty and developments in tech-sector could serve as pervasive forces affecting stock returns in the US for the period from 2005 to 2017. To isolate shocks associated with these factors we estimate the residuals of ARMA models, arguing an assumption of random walk processes implied by several previous surveys could lead to spurious results due to the presence of significant autocorrelation. Moreover, we implement a Fama-MacBeth (1973) variant procedure to estimate the risk premiums where the cross-sectional regressions are substituted by a panel data analysis with time-varying factor loadings assuming premiums remain time-invariant throughout the testing period. To support our empirical tests, we have constructed two algorithms; the first one arranges stocks into portfolios upon three different criteria (exposure to market risk, market capitalization and industry) while the second estimates exposures of returns to the factors with a rolling window technique. Considering annual returns and allowing exposures to vary per annum, we corroborate our findings with the three different techniques of portfolio formations and the model explains approximately one-third of stock prices fluctuation. When we reduce the time-horizon of returns to one month (increase the frequency of observations) and allow risk exposures to change per month, we find that the estimated premia are quite sensitive to both the subperiod we set and the technique behind the portfolio formation. Sign and magnitude of premiums are at least plausible.

Keywords:

Arbitrage Pricing Theory; Asset pricing; Multifactor model; Macroeconomic factors; Pervasive forces; Systematic risks; Stock returns; Shocks; Algorithms; Panel data.

Contents

Section 1. «Introduction»

What the modern portfolio theory teaches us is, in a world of risk-averse investors who trade assets in a frictionless economy attempting to maximize their wealth, their reward is associated with the co-variability of the tradeable assets' returns. Diversifiable risks are eliminated in their well-diversified portfolios and thus compensations are a function of the forces which influence broadly the returns on assets, namely pervasive forces. The identification of these forces has long occupied scholars. The most widely discussed theory, namely Capital Asset Pricing Theory (CAPM), introduced by Sharpe (1964), Lintner (1965) and Mossin (1966) assumes that securities expected returns are affected by the expected returns on a portfolio of all assets in the economy, the market portfolio. Unfortunately, all researchers who tested the theory used returns on a market index as a proxy for the market portfolio and implicitly assumed the index was efficient. Opponents of CAPM also criticize its restrictive assumptions (i.e. returns are normally distributed and investors can lend and borrow unlimited amounts of the riskless asset). Arbitrage Pricing Theory (APT) developed by Ross (1976) offers an alternative of -and often regarded as a general theory behind- the CAPM with only a few assumptions imposed. If there is a linear process generating stock returns where the agents form their homogenous expectations, there is a large number of securities in the market so that well-diversified portfolios can be constructed and riskless profits are precluded, then the expected (ex-ante) returns of securities can be written as a linear function of returns on a riskless asset (or a zero beta portfolio) and the sum of risk premia associated with a number of (common) risk factors. Under Ross's theory (1976) the common variability of assets' returns can be caused by more than one factors. One of the strongest weaknesses of this theory though, is that it does not determine the number nor the identity of these factors. In an attempt to test the validity of APT, several factor analytic techniques have been applied by many researchers. Plenty of them were quite supportive (i.e. see Roll and Ross (1980) and Chen (1983)) whilst others pointed out further weaknesses or even cast doubt on the testability of the theory (i.e. see Dhrymes, Friend and Gultekin (1984) and Shanken (1982)). But the question remains, what causes fluctuations systematically on securities returns?

From the middle of 1980s countless studies have attempted to answer the question using multifactor models with pre-specified factors. Chen, Roll and Ross (1986) in their seminal work identify five common risk factors in the US namely, unexpected growth of industrial production, unanticipated inflation and changes in expectations about inflation, changes in the risk premia (as measured by the difference in returns between risky corporate bond and government bond portfolios) and shifts in the yield curve, though the two inflation-related factors seem to influence stock returns in certain subperiods only. Since then, many researchers in the US and all over the world, fascinated by the multifactor model of Chen et al. (1986) tried out to construct an Arbitrage Pricing model with observable factors. Many of them give support to Arbitrage Pricing Theory and conclude that more than one factors affect stocks returns whilst many others do not find significant premia or express their concerns on the reliability of tests using observable factors when there is no theoretical background to support these relationships. Fama and French (1993) find that variables with no special meaning have predictive power to explain the cross-sectional variations of returns. Up to this point we can distinguish three general approaches attempting to answer the same question: The statistical approach, the macroeconomic approach and finally the fundamental approach. Connor (1995) finds the second rather weak when compared to the remaining two but admits it is the strongest in terms of economic reasoning.

In this study we implement the macroeconomic approach to test whether six candidate factors could stand as legitimate APT factors in a multifactor model. These factors are shocks related to industrial production growth, inflation, movements of default spread, shifts in the slope of the yield curve, intensity of policy-related uncertainty and developments in tech-sector. Specifically, our research question is, do realizations of these factors predict stock prices in the US for the period from 2005 through 2017? Instead of forming mimicking portfolios to capture these factors separately, we use observable variables and derive their shocks to further test their influence. We claim, consistent with the findings of Priestley (1996), that the *rate of change* approach implemented by several previous studies to isolate unexpected components of the macro-variables, by only assuming their series follow a random walk process is econometrically wrong as lags of the series have found to have predictive power in most cases and thus, we derive factor realizations as the residuals of ARMA models. All candidate factors should be mean-zero serially uncorrelated white noise processes and do not expose severe correlation with each other. After a rigorous examination of these conditions, we estimate our results to be more reliable than those in studies like Chen et al. (1986), Chan et al. (1985), Hamao (1988), Azeez and Yonezawa (2006) etc. Relevant studies used a Fama-MacBeth (1973) variant technique to derive the risk premia which seems not applicable within short subperiods as the test statistics give spurious results with inadequate degrees of freedom (especially when independence across observations is not maintained) and is also not indicative in the sense that t-statistics estimate significance of each factor separately but not the entire model. Based on Elton et al. (2003) if following the macroeconomic approach, one performs a joint test. Consequently, we suggest a variant of this technique where the "second-pass" cross-sectional regressions are substituted by a panel data analysis allowing for time-varying factor loadings and assuming risk premiums remain constant throughout the testing period. Using this technique, we can estimate both the model and the prices of risks simultaneously and further convert the pricing model to a conditional one. As these techniques are exposed to an errors-in-variables problem due to the fact that factor loadings entering the model are estimations rather than the real (unknown) parameters, our testing assets are portfolios rather than individual stocks. But if different portfolio formations result in different pricing models, this technique reveals another major disadvantage. In our knowledge, only Clare and Thomas (1994) address this potential problem, and indeed have found that the criteria behind the portfolio formation really matters. To corroborate our results, we use three different criteria to arrange securities into portfolios; based on securities exposure to market risk, based on their market capitalization and finally depending on their industry.

Considering annual returns in the "second pass" panel regressions and allowing exposures to vary per annum, we corroborate our findings with the three different techniques of portfolio formations. Based on our results, all factors carry significant premiums except for policy-related uncertainty of which effects have already been captured by the two bond-market factors, namely default yield spread and term structure. Our proposed five-factor model explains approximately one-third of stock prices fluctuation. When we increase the frequency of observations though, by reducing the time-horizon of returns to one month, and allow risk exposures to change per month, we find that the estimated premia are quite sensitive to both the subperiod we set and the technique behind the portfolio formation. Sign and magnitude of premiums are at least plausible.

The work behind the portfolio formation and the “first-pass” time series regressions has been supported by two algorithms we have constructed and presented in Appendices A and B. Consequently, all our results are easy to confirm and further, we enhance future research in this area to identify risk factors in every economy. Given input data relative to securities, the user gets three types of portfolios, industry portfolios, market-capitalization sorted portfolios and portfolios sorted by their exposure to market risk. The user specifies how many portfolios to construct on the two later types. Moreover, given the candidate factor realizations as well as a proxy for the risk-free rate the second algorithmic code derives all factor loadings with a rolling window technique and provides the user with matrices which are ready to test in a panel or cross-sectionals form. If further, returns of a market index are given, the code can produce realizations of an unobserved factor, called residual market risk (see Burmeister and Wall (1986)) and include it in the model, upon the user’s request.

The rest of the thesis is as follows. In Section 2 we introduce the reader to the modern portfolio theory and in Section 3 we present in short, the Capital Market Theory and thereinafter the development of Arbitrage Pricing Theory. In Section 4 we make a reference to the three alternative models, which have been used extensively in the literature to derive the risk premia and present the candidate factors we used in this study. In Section 5 we describe the data and methodology we followed. In Section 6 we present our results, followed by some warnings and suggestions for future researches in Section 7, only to conclude in Section 8.

Section 2. «A Synopsis of Modern Portfolio Theory»

2.1 Markowitz Mean – Variance Analysis

Modern Portfolio Theory was pioneered by Harry Markowitz in his paper Portfolio Selection, published in 1952 on the Journal of Finance. The main idea of this theory is, assuming that investors are risk-averse, there is a (common) efficient frontier of optimal portfolios to all investors offering the maximum possible expected return for each level of risk.

Before presenting this theory as a precursor to the development of asset pricing theory, it may be optimal to discuss some general assumptions of portfolio theory and the basic tools needed as well. One basic assumption is that investors desire to maximize the returns on their investments for a given level of risk. In example, given two securities bearing the same level of risk, but offer different expected returns, investors would prefer to hold the one which gives higher expected returns. In addition, portfolio theory assumes that investors are basically risk-averse, meaning that they attempt to lower the uncertainty. In order to avoid any ambiguity on this term, risk aversion does not mean that investors are not willing to hold any risky asset on their portfolios, but they require higher returns on this asset comparing to an asset free of risk. In example, given two securities which have almost the same returns but are exposed to different risk levels, an investor would rather sell the more-risky security and buy the less-risky one. Having assumed risk aversion as a behavioral characteristic of investors, we are able to support that there is a trade-off between uncertainty and returns, or better, there is a positive relation between the expected return and risk, meaning that the riskier a security is, the greater the possibility of higher returns.

A reasonable question that arises however is, how do we define risk? Although risk and uncertainty do not have the same meaning, we could define risk as the uncertainty of future outcomes. Moreover, risk involves the possibility the actual returns of an asset will differ from the expected respectively. It also involves the possibility of losing part or all of the initial investment. As there is no standard definition of risk, there is also no specific measurement of it. In the field of finance, there have been used different measures over time such as the standard deviation of the expected returns, and the beta coefficients depending on the purpose we study.

An initial step before someone makes decisions in finance is to determine the environment under which he/she invests money. Generally, we could specify four conditions/states based on how uncertain an investing environment is:

1. Under the *state of certainty*, we identify the exact outcome of an investment and we are not exposed to any risk of losing money.
2. Under the *state of riskiness*, there are many (known) potential outcomes each of which has a specific probability to occur. Under this condition, investors are able to measure the risk and return by exploiting data from the probability distribution. Notice that the sum of all probabilities equals one.

3. Under the *state of uncertainty*, there are many potential outcomes known in advance, but we are not able to determine their probabilities. Investors may use subjective probabilities under this condition.
4. Finally, under the *state of ignorance*, we are not able to (objectively) determine, the potential cash flows and their relevant likelihood to occur.

Dating back before the contribution of Markowitz on Modern Portfolio Theory, investors community suffered from the lack of a common measure of risk and decisions depended almost solely to the expected return estimations. In his analysis, investors take into account the first two moments of asset returns. These are, the expected returns and the variance of returns. There is an extensive description of these moments on a single stock and a portfolio of assets as well, before presenting the efficient frontier of portfolios defined by Markowitz. The assumptions imposed by Markowitz under his basic model for expected returns and the standard deviation for a portfolio of assets are the following:

1. Investors assess and choose among alternative investments by their probability distributions of expected returns.
2. Investors seek to maximize their single-period utilities.
3. Investors define risk as the variability of expected returns.
4. Investors base their decisions solely on expected return and risk.
5. Investors always prefer higher to lower returns for a given level of risk and less to more risk for the same level of expected returns. Therefore, all investors behave rationally.

Further, following Markowitz's idea an investment on a portfolio of assets consists of 4 steps:

1. Analysis of assets in terms of their returns and risk.
2. Assets combination and portfolios creation.
3. Efficient frontier construction.
4. Portfolio selection through the efficient frontier that best fits with the investor's utility curve.

2.2 Stock Return and Risk

Investors often use *historical* measures when estimate the *expected* rates of return and risk. Consider a single share of stock. The historical rate of return of this stock is given by the following equation:

$$R_{it} = \frac{P_{it} - P_{it-1}}{P_{it-1}} + \frac{D_{it}}{P_{it-1}} \tag{2.1}$$

where R_{it} is the rate of return of stock i, P_{it} is the price of stock i at time t, P_{it-1} is the price of stock i at time t-1 and D_{it} is the dividend of stock i paid at time t. The above equation implies that the total stock return can be decomposed into two parts. The first part of the right-hand side of this equation is the *capital gains yield* and the second one is the *dividend yield*. Now, assuming we have T observations of returns on stock i, then the average (historical) rate of return is computed as:

$$\bar{R}_i = \frac{1}{T}\sum_{t=1}^{T} R_{it} \tag{2.2}$$

where the observations t=1, 2, …, T should be equally distributed over time (i.e. t may refer to daily, weekly, monthly, annual returns, etc). Assuming now, that we want to estimate the expected (future) returns of a stock in a state of riskiness where we possess a probability distribution of potential returns, then the expected returns of the stock could be estimated using the following equation:

$$E[R_i] = \sum_{j=1}^{k} P_j \cdot R_{ij} \tag{2.3}$$

where $E[R_i]$ is the expected rate of return of stock i, R_{ij} is the jth potential rate of return of stock i and the P_j is the probability that R_{ij} occurs. Notice that in a (theoretical) state of certainty $E[R_i]$ equals R_i as there is (only one) certain outcome.

Having estimated the average return of the stock, we can now calculate the variance (and the standard deviation) of the returns of this stock. The (historical) variance is given by the following equation:

$$V_{ar}(R_i) = \frac{1}{T-1}\sum_{t=1}^{T} (R_{it} - \bar{R}_i)^2 \tag{2.4}$$

where $V_{ar}(R_i)$ denotes the variance of the returns of stock i, and can also be symbolized as $\sigma^2_{R_i}$. In case we use expected stock returns rather than ex post data, the equation of variance is:

$$V_{ar}(R_i) = E[(R_i - E[R_i])^2] = \sum_{j=1}^{k} P_j \left(R_{ij} - E[R_i]\right)^2 \tag{2.5}$$

Notice that in a condition of perfect certainty the variance of the security equals zero, meaning that there is no possibility that the actual outcome differs from our expectations. The standard deviation, which is widely used as a measure of risk is simply the square root of variance:

$$\sigma_{R_{it}} = \sqrt{V_{ar}(R_i)} \tag{2.6}$$

Other measurements of expected returns, and risk have also been presented in the literature, i.e. the geometric mean and the semi-variance, but these are far beyond the purpose of this study. Of course, in most cases investors do not hold only one type of securities at their portfolios. They use to hold a variety of securities and they are interested of their portfolio performance. A simple reason is the fact that they want to succeed diversification in order to reduce their risk exposure. Suppose a portfolio which involves *n* securities. The historical rate of return of a portfolio equals to:

$$\bar{R}_P = \sum_{i=1}^{n} w_i \bar{R}i \tag{2.7}$$

where $\bar{R}_P$ is the total rate of return of the portfolio, p, in a specific time, w_i denotes the weight of security i and is the value invested on security i over the total value invested on portfolio p and $\bar{R}i$ is the historic average rate of return of security i. Similarly, the expected rate of return of a portfolio can be estimated by the following equation:

$$E[R_P] = \sum_{i=1}^{n} w_i E[Ri] \tag{2.8}$$

The right-hand side of the above equation denotes that the expected rate of return of a portfolio of investments is the weighted average of the expected rates of return of the individual securities in the portfolio. Note also that the sum of all weights equals one:

$$\sum_{i=1}^{n} w_i = 1$$

Even if the calculation of the expected rate of returns seems to be easy, this is not the case of the variance estimation of the overall portfolio performance. Assume that a portfolio contains only two securities, say A and B. Then the variance of this portfolio is:

$$\sigma_{R_P}^2 = w_A^2\, \sigma_A^2 + \; w_B^2\, \sigma_B^2 + 2\, w_A\, w_B\, \sigma_{AB} \tag{2.9}$$

where w_A (w_B) is the weight of asset A (B), σ_A^2 (σ_B^2) is the variance of asset A (B) and σ_{AB} is the covariance of assets A and B given by the equation:

$$\sigma_{AB} = \frac{1}{T-1} \sum_{t=1}^{T} (R_{At} - E[R_A])\,(R_{Bt} - E[R_B]) \tag{2.10}$$

Given that the correlation of the returns of two assets equals the covariance of such assets over the product of their standard deviations, the variance of the portfolio could be written as:

$$\sigma_{R_P}^2 = w_A^2\, \sigma_A^2 + \; w_B^2\, \sigma_B^2 + 2\, w_A\, w_B\, \rho_{AB}\, \sigma_A\, \sigma_B \tag{2.11}$$

where the correlation:

$$\rho_{AB} = \frac{\sigma_{AB}}{\sigma_A \sigma_B} \tag{2.12}$$

can be easily proven to take values between -1 and 1.

A careful observation of the equation which gives the variance of a portfolio explains why investors prefer to allocate their money to various investments. Assume that the correlation of returns of assets A and B equals one, meaning there is a perfect (positive) correlation of these assets. Then, it can be easily proven that the portfolio's standard deviation equals the weighted average of the individual standard deviations of assets A and B. Given a correlation below one however, results in a lower standard deviation of the portfolio. In such a manner, the investor benefits from the diversification as he constructs a portfolio with no-perfectly correlated securities and succeeds to reduce his exposure to risk. In real world, investors hold much more securities on their portfolios to succeed even better diversification. The variance of the portfolio of n assets can be given by:

$$\sigma_p^2 = \sum_{i=1}^{n} \sum_{j=1}^{n} w_i\, w_j\, \sigma_{ij} \qquad \forall\, i, j$$

or

$$\sigma_\rho^2 = \sum_{i=1}^{n} w_i^2 \sigma_i^2 + \sum_{i=1}^{n} \sum_{j=1}^{n} w_i\, w_j\, \sigma_{ij} \qquad \forall\, i \neq j \tag{2.13}$$

where *i* and *j* do not refer to the same security. The standard deviation (σ_ρ) of such a portfolio is the square root of its variance.

2.3 Efficient Portfolios

Markowitz showed that investors should not consider the individual asset returns solely but should focus on the characteristics of their portfolios, which is, the combination of all assets they hold. Under the assumptions he set, a portfolio of assets (or an asset) is said to be *efficient* if no other portfolio (or asset) offers higher expected return with the same or lower level of risk. Alternatively, the efficiency can be defined if there is no other asset or portfolio of assets which offers lower risk with the same or higher expected return. Assume there only exist two stocks on the market, called A and B. Figure 2.1 presents the case of four curves of portfolios contain only stocks A and B with different weights. Each curve on the graph differs one another as the correlation of the two stock returns differ. Clearly, if there is a perfect correlation between the stock returns of A and B (ρ=1), the curve is a straight line.

Figure 2.1

This line graph represents how the feasible set of portfolios changes in a world of two assets, under different correlations (i.e. perfect negative, no correlation, when the returns on two assets are correlated by 50% and when they are perfectly correlated). Vertical axis is related to expected portfolio returns and horizontal axis is the standard deviation of these returns. An assumption that short-selling is not allowed was imposed.

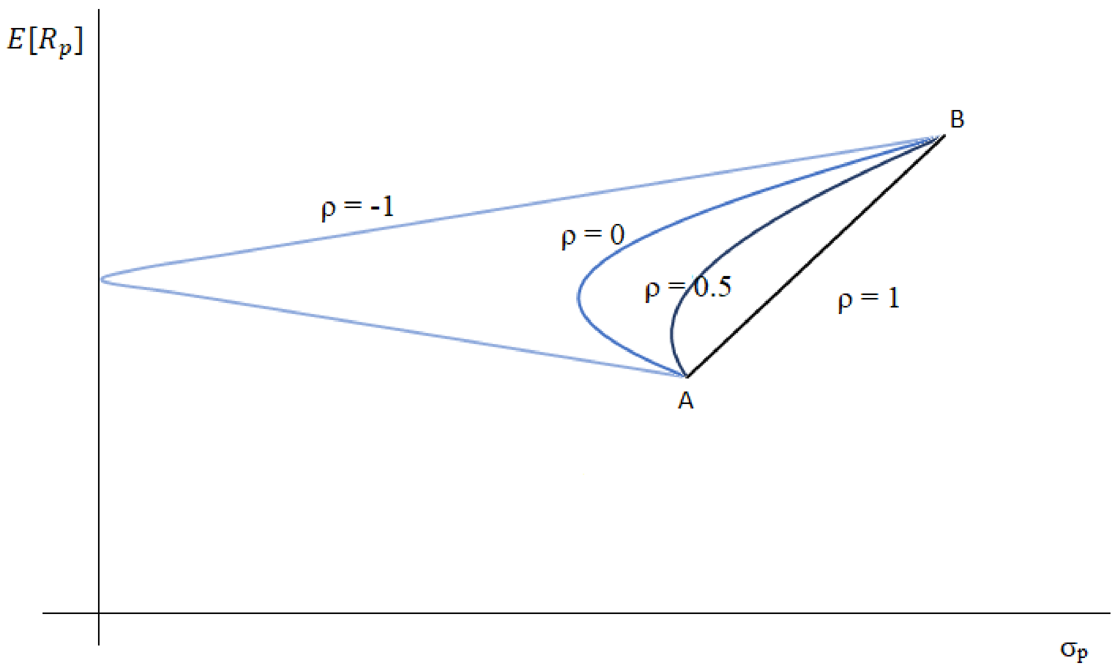
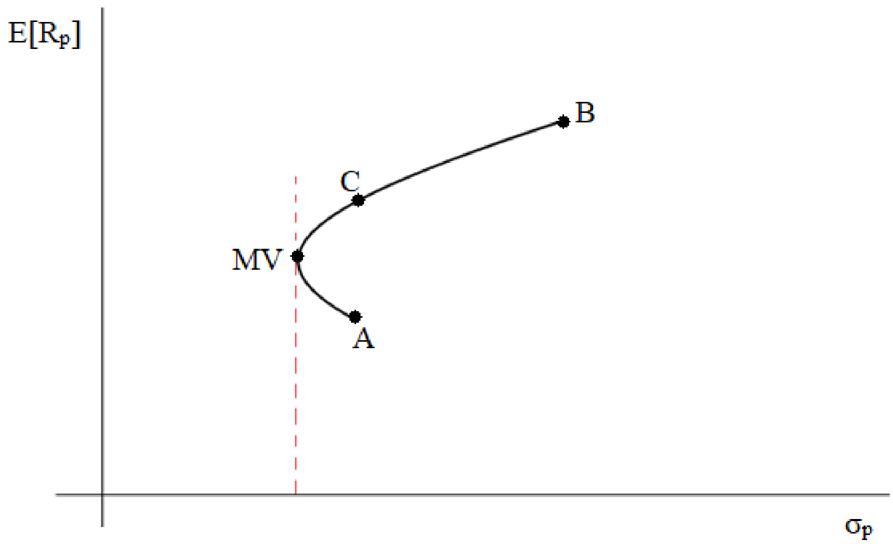


Figure 2.2 presents one curve of portfolios of two stocks A and B on the dimensions of expected return and standard deviation. The returns on these two stocks are positively (but not perfectly) correlated. Curve AB is called *opportunity set* or *feasible set* and contains all the potential combinations of these stocks forming a portfolio. Spot A, in example, denotes a portfolio made up of 100% stock A and 0% stock B. Spot B, is a portfolio constructed only by stock B likewise. On spot MV, weights of A and B form the portfolio with the minimum variance (and the minimum standard deviation by definition).

Figure 2.2

This line graph depicts a feasible set of portfolios of two stocks, A and B, when return on these stocks are positively correlated. Vertical axis is related to expected portfolio returns and horizontal axis is the standard deviation of these returns. An assumption that short-selling is not allowed was imposed. All spots onto the curve AB denote a portfolio with different portions invested on assets A and B. MV portfolio is the one with the minimum variance. Spot A (B) represents a portfolio which consists 100% of asset A (B).



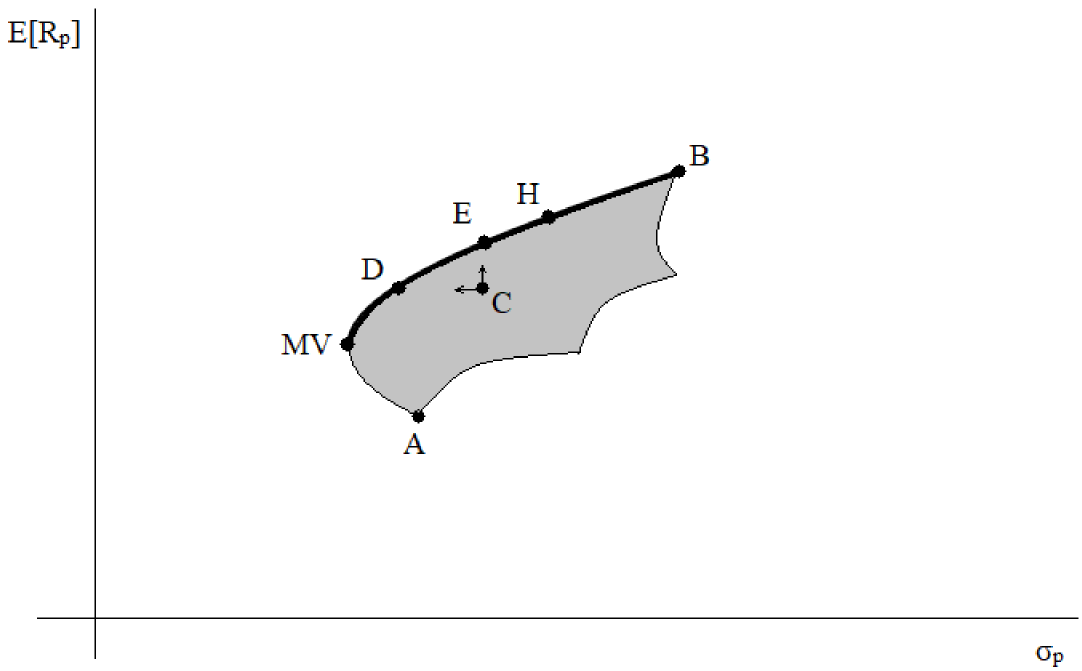
Notice that Portfolios A and C have the same risk but different expected returns. Based on Markowitz's assumptions, all (rational) investors would prefer to hold portfolio C rather than A as it maximizes their expected returns. Therefore, investors are rationally interested only to the part of the curve between spots MV and B, which is called the *efficient set* or *efficient frontier*. Efficient frontier contains all the potential portfolios consisting of stocks A and B, which are *efficient portfolios*. As a matter of fact, we are not able to distinguish a portfolio on the efficient set as the portfolio with (objectively) better characteristics than the others on the same set. The *optimal* portfolio, or alternatively, the efficient one that is desirable by an investor depends on how risk averse the investor is. In example, a more risk averse investor is more likely to select portfolio C, or even better portfolio MV, rather than portfolio B as he/she intends to avoid risk. By contrast, a less risk averse investor may find that portfolio C suits better to his/her own preferences than portfolio MV. The role of *utility functions* is to describe investors' preferences.

The efficient frontier of portfolios consisting of more than two stocks is the curve connecting spots MV and B, given in figure 3. For simplicity we have assumed that no short-selling is allowed. There are almost infinite combinations of assets which construct portfolios in this case and hence, all the shaded area is covered by the portfolios. Notice that in case of two-assets, portfolios were restricted only upon the curve AB. What is more, when there is no restriction on short-selling stocks, portfolios exist with expected return higher than of this graph, but also, their volatility exceeds the volatility of stocks within it and the curve changes somewhat. Something that can be said with confidence about portfolios onto the efficient frontier is, given a certain level of risk, there is no portfolio with higher expected return than the efficient portfolio on this set. Under the

Markowitz's assumptions, portfolio C is not an efficient one, as there exist other portfolios with higher expected return over the same (or lower) level of risk. Portfolios MV, D, E, H and B on the curve are all efficient, as they offer the maximum expected returns over their unique standard deviation.

Figure 2.3

The following curve depicts the efficient frontier as well the feasible set of portfolios, constructed by more than two assets, when short-selling is not allowed. Vertical axis is related to expected portfolio returns and horizontal axis is the standard deviation of these returns. All shaded area represents the *feasible set* of portfolios whilst the curve which connects the spots MV and B is the *efficient frontier*. MV is the portfolio with the minimum variance.



To present Markowitz's arguments in algebraic terms, assume an equal weighted portfolio of assets. The term "equal-weighted" means that we have invested the same amount of money to buy all of the stocks in this portfolio, and hence their contribution is commonly (1/n). Then the equation (2.13) can be written as:

$$\sigma_\rho^2 = \sum_{i=1}^{n} \left(\frac{1}{n}\right)^2 \sigma_i^2 + \sum_{i=1}^{n} \sum_{j=1}^{n} \left(\frac{1}{n}\right)^2 \sigma_{ij} \quad \forall\, i \neq j$$

or better,

$$\sigma_\rho^2 = \frac{1}{n}\sum_{i=1}^{n} \frac{1}{n}\, \sigma_i^2 + \sum_{i=1}^{n} \sum_{j=1}^{n} \left(\frac{1}{n}\right)^2 \sigma_{ij} \quad \forall\, i \neq j \qquad (2.14)$$

which finally equals,

$$\sigma_\rho^2 = \frac{1}{n}\,\overline{\sigma_i^2} + \sum_{i=1}^{n}\ \sum_{j=1}^{n}\ \left(\frac{1}{n}\right)^2\ \sigma_{ij} \quad \forall\ i \neq j \tag{2.15}$$

where $\overline{\sigma_i^2}$,is the averaged variance of the stocks included in the portfolio. The first part of the right-hand side of the above equation tends to zero as the number of assets, *n*, gets an almost infinite number, meaning that when *n* becomes large enough, the most significant contribution of portfolio variance is the second part of the right-hand side. Hence, in a large portfolio of assets, idiosyncratic disturbances affecting individual stock returns become no important sources of portfolio risk (as we may see in the next section). Instead, the covariance of each pair of stocks has significant effects on the total portfolio variance. This observation reveals both how important Markowitz's analysis is and what investors really concern when constructing or reforming portfolios. The benefits they exploit by diversifying are very important.

2.4 Benefits of Diversification

Consider a firm listed on a Stock Exchange market. Every moment, its stock return (R) is consisted of two parts, the expected return ($\bar{R}$) and the unanticipated return (U):

$$R = \bar{R} + U \tag{2.16}$$

The first part can be estimated by using any information relevant to the certain stock and the issuer firm. For example, when the Board of Directors announces a dividend payment, this information will be taken into consideration by investors who are interested on the stock. It is easy to consider the second part as a set of events that influence the stock price and no information has been revealed yet in order to make these events predictable. A sudden reduce on interest rates by the Central Bank, a destruction in the production line and CEO's replacement are examples of such events. The unexpected part of total returns carries the risk of real returns to differ from the expected ones. On the other hand, the expected returns have been estimated in a way that all of the available information has counted on. The real risk of stock returns (which is the unanticipated returns) can be decomposed into two parts, the *systematic* risk and the *unsystematic* risk. The first one, which is often referred as market risk as well, is the risk affecting a large number of securities, regardless the volume of effect. The second, is also called *idiosyncratic* risk or *diversifiable* risk and affects only the price of a certain security or a minor group of securities at most. Examples of systematic risk is the uncertainty about changes in interest rates, the exact level of inflation, the GDP official announcement, etc. Examples of unsystematic risks can be a strike in the company, an injury etc. Sometimes it's hard to distinguish these two risks as a minor event can eventually affect more industries. Hence, the unanticipated risk (U) can be written as a sum of the systematic (m) and non-systematic risk (ϵ) and the total returns are:

$$R = \bar{R} + m + \epsilon \tag{2.17}$$

Notice that ϵ is specific to the firm and therefore must be uncorrelated to other firm's so-called risk. By definition, ϵ can be diversified in a portfolio of stocks. Figure 2.4 presents in generality, how the risk of returns of a portfolio of stocks (measured by the standard deviation) decreases as the number of stocks included in this portfolio increases (we can make an assumption that m influences on the same volume all the stocks to simplify the graph). The reason is that, since each stock's idiosyncratic risk is uncorrelated to all the other stocks, the positive ϵ's will offset the negative ones and the unsystematic risk of the portfolio is lesser than the unsystematic risk of the stocks. Moreover, when the portfolio is constructed by a significantly large number of different stocks the portfolio's ϵ tends to zero. An algebraic explanation is, assuming a portfolio of stocks with equal weights ($w_i = 1/n$) and a single factor model (more about this model is presented below), the non-systematic portfolio variance will be:

$$\sigma_{e_\rho}^2 = v_{\alpha r}\left(\sum_{i=1}^{n} w_i e_i\right) = \frac{1}{n^2}\sum_{i=1}^{n} \sigma_{e_i}^2 = \frac{1}{n}\sum_{i=1}^{n} \frac{\sigma_{e_i}^2}{n} = \frac{1}{n}\,\bar{\sigma}_{e_i}^2 \tag{2.18}$$

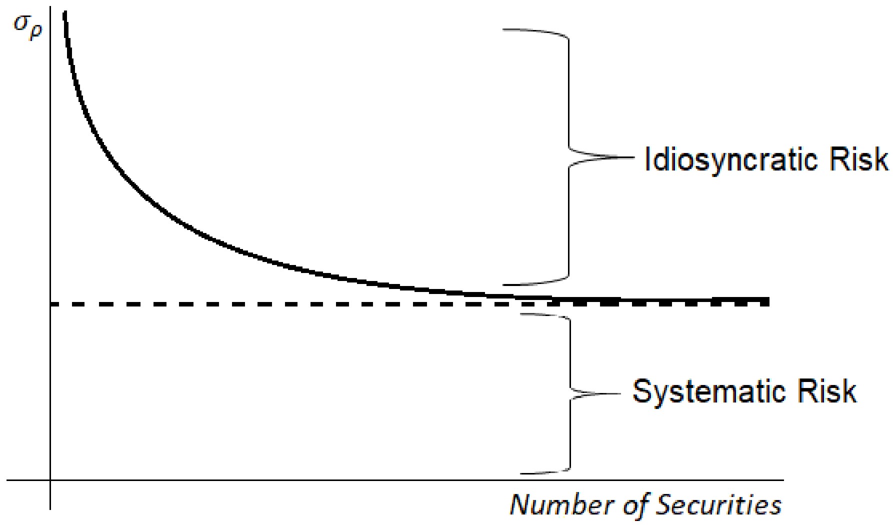
To derive the above relationship, we have assumed that the firm-specific variance components are uncorrelated. As we can see, the greater the number (n) of selected stocks in the portfolio, the lower the mean variance of $e_i's$.

Consequently, we expect rational investors to be attracted to well-diversified portfolios. They can eliminate a part of risk by adding more stocks. They cannot diversify the market risk though, and that is an explanation why they are not able to eliminate the total risk. Ultimately, they may succeed to better reduce risk by investing in foreign markets as well, since the foreign market conditions are different to the domestic ones. Notice that on the same graph, the systematic risk does not change at all when more stocks are added to the portfolio (under the assumption of all stocks being equally exposed to the market risk). In order to reduce this risk investors would use hedging techniques. In fact, though, different assets are not exposed the same to the market risk.

To conclude, three components determine a portfolio variance, each asset's variance; the covariance between each pair of assets and finally the weights invested on each asset. The second component surpasses in significance the first one. The more we increase the number of securities in a portfolio, the more we are concerned about the additional security's covariance with the other assets included, rather than its total variance.

Figure 2.4

The following graph reveals the relationship between the total standard deviation of returns of a portfolio of assets and the number of assets that constitute the portfolio. When the number of assets increases, standard deviation of portfolio returns is reduced due to the diversification. An assumption of equal weights invested was imposed. When the portfolio consists of an infinite number of assets, portfolio returns vary due to non-diversifiable risks only.



Section 3. «Capital Market Theory and the Development of APT»

3.1 Development of Models

What have we seen so far is, to define the efficient frontier we must be able to determine the first two moments (expected return and variance or standard deviation) of return on a portfolio. These are given by (2.8) and (2.11). Unfortunately, if we analyze a large number of stocks (say *n*) as candidates for our portfolio inclusion we may need *n* (*n*-1)/2 estimations of the pairwise correlation between all stocks. Hence, it seems unlikely that we are able to estimate correlation structures in a direct way. Many models however have been developed to forecast correlation structures. These models can be separated into two categories, index models and averaging techniques.

3.1.1 Single- Index Model

Sharpe's (1963) Single-Index Model is the most widely used technique. This model is a return-generating process which is often used in estimating the correlation matrix as well as to test the market efficiency and equilibrium. The thought is, the co-movement between stocks arises from a single common influence (or index). Indeed, we may observe that when the market goes up, most stocks also tend to increase in price, and vice versa. This suggests that one reason why returns from various stocks are correlated is because of a common response when the market changes. Therefore, we may use the following analysis to identify a useful measure of the correlation between the return on a stock and the return on a stock market index. Suppose that the return of a stock i, is a linear function of the return of a market index *m*:

$$R_i = a_i + \beta_i R_m \tag{3.1}$$

where,

a_i is a random variable related to the component of return of stock i which is independent of the market performance,

β_i is a constant coefficient which refers to the sensitivity of the returns of stock i to the market index returns and

R_m is the market performance (random variable) as measured by the returns of the index *m*.

The term a_i can be decomposed into two parts:

$$a_i = \alpha_i + e_i \tag{3.2}$$

where α_i represents the expected value of a_i and e_i is the unanticipated return of a_i. Therefore, the basic equation of this model can be written as:

$$R_i = \alpha_i + \beta_i\, R_m + e_i \tag{3.3}$$

where we assume that e_i is a mean-zero, E[e_i]=0, and that market index return is uncorrelated to the error term, meaning that Cov(R_m, e_i) = 0. Moreover, a key assumption of this model is E[$e_i e_j$]=0, which means that e_i is independent of e_j for all values of $i \neq j$. Under this assumption the only reason we observe a co-movement on stocks is because of their common factor, the market and hence, there are no other effects beyond the market that influence stocks to co-move. Notice that $\alpha_i + e_i$ is the component of the return due to the (stock i issuer) firm's activities and is called *non-systematic return*. Factors affecting non-systematic returns may be the firm's management, R&D of the firm, etc. On the other hand, $\beta_i\, R_m$ is the term affected by the market and is called *systematic return*. By definition, the variance of e_i equals $E[e_i^2] = \sigma_{e_i}^2$ and the variance of R_m is $E[R_m - \bar{R}_m]^2 = \sigma_m^2$. From equation (3.3) we derive the expected return of stock i. Bearing in mind the first assumption, we have:

$$E[R_i] = \alpha_i + \beta_i \cdot E[R_m] \tag{3.4}$$

It is also easy to prove that the variance of stock i returns equals:

$$\sigma_{R_i}^2 = \beta_i^2 \sigma_{R_m}^2 + \sigma_{e_i}^2 \tag{3.5}$$

By observing (3.4) we may defend that the expected returns of a stock, i, can be decomposed into two parts. Alpha coefficient is the non-systematic anticipated returns of stock and $\beta_i \cdot E[R_m]$ gives the systematic contribution on the expected returns of the stock. In a similar way, the risk of stock i returns can be separated into two components. On the right-hand side of (3.5), $\sigma_{e_i}^2$ is the non-systematic risk, called also idiosyncratic risk and $\beta_i^2 \sigma_{R_m}^2$ is the systematic contribution of risk to the total risk of stock i returns. It can be also be proven that:

$$Cov(R_i, R_m) = \beta_i \sigma_{R_m}^2 \tag{3.6}$$

Suppose now another stock, j. In order to extract the co-movement of returns of two stocks, the proceed is as follows:

The covariance between the two stocks can be written as:

$$Cov\left(R_i, R_j\right) = E\left[(R_i - \bar{R}_i)\left(R_j - \bar{R}_j\right)\right] \tag{3.7}$$

where R_i and R_j can be given by equation (3.3) and the mean returns $\bar{R}_i$ and $\bar{R}_j$ can be found by (3.4) respectively. Hence with the substitution of equations (3.3) and (3.4), we may find that

$$Cov\left(R_i, R_j\right) = \beta_i\, \beta_j\, \sigma_{R_m}^2 \tag{3.8}$$

and the correlation coefficient (as presented in (2.12)), is:

$$\rho_{ij} = \frac{\beta_i\, \beta_j\, \sigma_{R_m}^2}{\sigma_i\, \sigma_j} \tag{3.9}$$

Obviously, if the single index model is an appropriate model, beta coefficients can be effectively used to derive an approximation of the correlation between two stocks, or securities in general. Recall that, as mentioned above, it seems impossible to directly estimate correlation structures when we want to analyze a large number of stocks. Another interpretation of (3.9) is that, given the correlation coefficient of two stock returns, we are able to test the efficiency of beta estimators.

3.1.2 Multi- Index Models

Single index model is based on the assumption that stocks' co-movement is due to the market changes only. There are two other approaches however, which have been used to derive an estimation of the stock returns correlation structure. These are multi-index models and averaging techniques. The main idea of multi-index models, is, there are other factors in addition to the market that account for the co-movement of the stock returns. An adverse scenario, however, when adding other indices, is that they are potentially picking up random noise rather than really influence the co-movement. In contrast, averaging techniques try to solve this problem by smoothing the entries in the historical correlation matrix. We should not defend however that the lastly mentioned technique gives more reliable results as real information may be lost in that process. A general multi index model can be given by the following basic formula:

$$R_i = a_i + b_{i1}\, I_1 \, + b_{i2}\, I_2 + \cdots + b_{iL}\, I_L + c_i \tag{3.10}$$

where,

I_j is the actual level of index j,
b_{ij} measures the sensitivity of stock i returns to the changes in index j and
c_i is the random component of the unique return.

We assume that c_i is a mean-zero, E[c_i]=0, and that market index return is uncorrelated to the error term, meaning that Cov(R_m, c_i) = 0. Moreover, a key assumption of this model is E[$c_i c_j$]=0, which means that e_i is independent of e_j for all values of $i \neq j$. Under this assumption the only reason we observe a co-movement on stocks is because of their common set of factors, and hence, there are no other effects beyond the market that influence stocks to co-move. In addition, we assume that Cov(I_i , I_k) = 0 for any $i \neq k$, meaning that the changes in all factors are uncorrelated to each other. In case where indices were uncorrelated (in the meaning of orthogonal matrices), it would be easy to compute risk and select optimal portfolios. This assumption is not a strict one, as it is possible to convert correlated indices to uncorrelated ones (econometrically).

Applying the same logic as in a single factor model we get the expected return and the variance of stock i, as well as the covariance of returns between two stocks $i\ and\ j$:

$$\bar{R}_i = a_i + b_{i1}\, \bar{I}_1 + b_{i2}\, \bar{I}_2 + \cdots + +b_{iL}\, \bar{I}_L \tag{3.11}$$

$$\sigma_{R_i}^2 = \beta_{i1}^2\, \sigma_{I1}^2 + \beta_{i2}^2\, \sigma_{I2}^2 + \cdots + \beta_{iL}^2\, \sigma_{IL}^2 + \sigma_{c_i}^2 \quad (3.12)$$

$$Cov\left(R_i, R_j\right) = \beta_{i1}\, \beta_{j1}\, \sigma_{I1}^2 + \beta_{i2}\, \beta_{j2}\, \sigma_{I2}^2 + \cdots + \beta_{iL}\, \beta_{jL}\, \sigma_{IL}^2 \quad (3.13)$$

The above formulas are generated by the general multi index model. Almost the same formulas are derived by the usage of an industry index model. In Industry index models we suppose the correlation between securities is caused by industry effects in addition to the market effect. Nevertheless, many authors have criticized the performance of multi-index models. Elton and Gruber found that the added indices introduced more random noise than real information into the forecasting process.

3.2 Capital Market Theory

Markowitz analyzed portfolio characteristics under a restriction that all tradable assets were risky. Many investors however tend to include “risk-free” assets in their portfolios. Assets that are free of risk have a promised rate of return with variance equal to zero. Treasuries, in example, can be considered such assets as the U.S government guarantees principal and interest to be fully paid. Practically speaking however, all assets have an (even trivial) exposure to risk.

Capital Market Theory, which is considered as an extension to Markowitz’s model, does take into account risky securities along with a security free of risk in portfolio analysis. The theory examines how should the assets traded in capital markets be evaluated. Many of models are included in the framework of this theory, with the most known being the Capital Asset Pricing Model. It extracts a relation between the expected return and risk of an efficient portfolio (if using CML), a relation between the expected return and risk of any security or portfolio (if using CAPM) and answers the question about which measure of risk is the most appropriate.

3.2.1 Assumptions of Capital Market Theory

There are some general assumptions imposed in Capital Market Theory’s models. These are:

1. Investors follow Markowitz’s idea, and therefore, they construct portfolios lying on the efficient frontier. The specific (efficient) portfolio they choose, nonetheless, depends on their risk-return utility function.
2. There is an asset free of risk, on which investors are able to borrow or lend money. Its rate of return is assumed to remain fixed regardless of the amount borrowed or lent.
3. All investors, when choosing to allocate their money on investments, have the same one-period time horizon.

4. Investors do not face any barriers on their investments. Hence, there are no transaction costs and taxes.
5. The environment is a non-inflationary, meaning that no inflation exists to influence investment returns, or the inflation is fully anticipated.
6. There are no information costs, and investors have access to the same information. Hence, there is no mispricing within the capital markets.
7. All investors have the same estimation of outcomes. The homogeneity of their expectations implies identical probability distributions for the expected rates of return.
8. There is the ability to buy or sell any amount of each security and all assets are infinitely divisible. As a result, an investor is able to buy or sell fractional shares of any asset or portfolio.

Under these assumptions, the market is in equilibrium and therefore all securities have a unique static price regardless the market they are traded in. Obviously, neither all these assumptions reflect the real world, nor we should judge a priori the predictive power any model, derived from this theory, may have.

3.2.2 Capital Market Line

It is much more convenient to reveal Capital Market Line along with figure 3.1. Under the first assumption of Capital Market Theory, all investors follow Markowitz's rules when analyzing the portfolio characteristics and they "designate" the efficient set of portfolios. In addition, since they exploit the same information (without any cost) and set the same time horizon, the efficient set is common to all investors.

Assuming a risk-free security, F, with its rate of return, R_F, we may derive a new set of efficient portfolios, since investors have the ability to lend (or borrow) money on this security. By definition:

$$E[R_F] = R_F \tag{3.14}$$

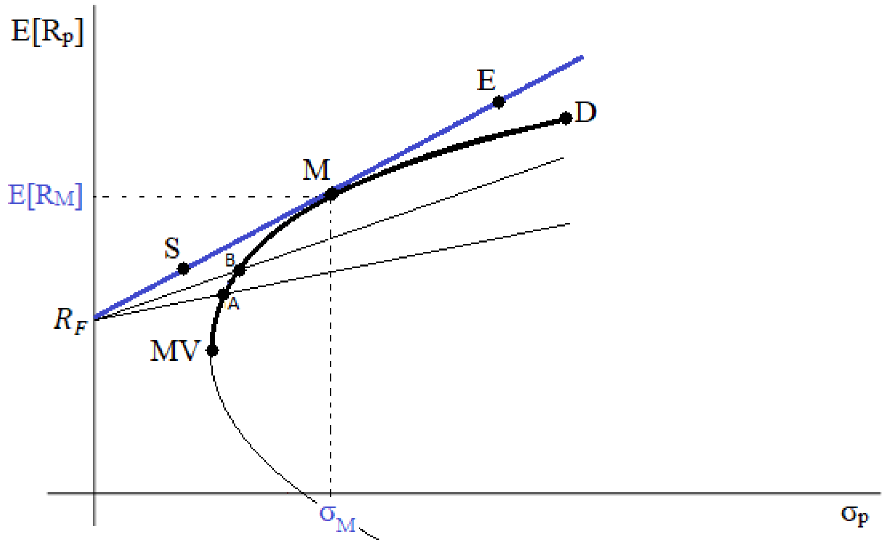
and

$$\sigma_{R_F}^2 = \sigma_{RF} = 0 \tag{3.15}$$

meaning that R_F is placed on the vertical line of figure 5. On the same graph, MV-D curve is the efficient frontier of Markowitz's analysis. A and B spots are selected randomly. If we design a line connecting the points R_F and A, we have constructed a new set of portfolios, involving the risk-free asset. Another line could be made using the B point instead of A.

Figure 3.1

The following graph depicts the *Capital Market Line* (CML) when short-selling is allowed. CML is the blue line starting from spot R_F and tangent to the market portfolio (spot M). R_F is the return on a riskless asset. Vertical axis is related to expected portfolio returns and horizontal axis is the standard deviation of these returns.



We may defend that the line segment (R_F – B) contains more efficient portfolios than (R_F – A), since these portfolios offer greater expected returns on the same risk. If we adopt this manner, by rotating the straight line passing through R_F in a counterclockwise direction we may conclude that the line connecting points R_F and M contains more efficient portfolios than any other line. This is the new efficient set of portfolios, called *Capital Market Line (CML)*. Notice that M is the tangency point between Markowitz's efficient frontier and the straight line passing through R_F. M is the *market portfolio*, that is, the one consisting of risky assets all investors would prefer to hold (under the theory's assumptions) without further referring to the investors' particular appetite for risk. CML is simply a set of efficient portfolios that can be derived from different proportions of invested capital on Portfolio M and the riskless security. Taking into consideration the investors preferences to undertake risk, the (R_F – M) segment and especially the points of this line near the R_F is much more preferable to more risk-averse investors, whilst the remaining segment of the straight line (the one above M) lies to risk tolerant investors. In example, portfolio S from this graph can be drawn by a combination of portfolio M and an investment on the riskless security. By doing so, an investor sacrifices a part of his portfolio expected return to reduce his risk exposure. On the other hand, portfolio E can be made by an investor who has borrowed some money at the risk-free rate and placed his money and the borrowed money on portfolio M. Holder of portfolio E resembles a more tolerant investor who is willing to invest more money on risky assets to maximize his returns.

As a result, all efficient portfolios are combinations of the riskless asset and the market portfolio (M). If there is a risky asset not included in M, then it would not have a value since the demand on this asset would be zero. The market portfolio is a well-diversified portfolio of risky assets and is the only one (on theoretical grounds) that investors find attractive when they are willing to undertake some risk. Algebraically, since all rational investors construct portfolios containing weights to the market portfolio and the riskless asset, their portfolio expected return would be:

$$E[R_P] = W_{RF}\, E[R_F] + W_M\, E[R_M] \Rightarrow$$

$$E[R_P] = W_{RF}\, R_F + (1 - W_{RF})\, E[R_M] \tag{3.16}$$

Both weights invested on the risk-free asset (W_{RF}) and the market portfolio (W_M) differ among investors as it is related to their risk tolerance, but the sum of these weights always equals one. A negative weight indicates borrowing money from this security/portfolio. Hence, any portfolio performance linearly depends on the market performance and the proportion invested on market portfolio. In addition, the riskiness of any portfolio is defined as:

$$\sigma_p = \sqrt{W_{RF}^2 \sigma_{RF}^2 + W_M^2 \sigma_M^2 + 2\, W_{RF}\, W_M\, \rho_{RF,M}\, \sigma_{RF}\, \sigma_M} \Rightarrow$$

$$\sigma_p = \sqrt{W_M^2 \sigma_M^2} = W_M\, \sigma_M \tag{3.17}$$

Obviously, there is no correlation between the market portfolio and the riskless asset ($\rho_{RF,M}$) since the outcome of the riskless asset is certain and do not vary on changes of the market performance. Geometrically, Capital Market Line has a positive slope. Indeed, $\frac{E[R_M]-R_F}{\sigma_M}$ is a positive number since the expected rate of return of the efficient portfolio M is greater than the risk-free rate of return and standard deviations are always positive numbers. We may use again the random efficient portfolio S, to extract a relation between the expected rate of return and risk of an efficient portfolio. Obviously, the slope referred to portfolio S equals the CML's slope since it is placed on the same line:

$$\frac{E[R_M] - R_F}{\sigma_M} = \frac{E[R_S] - R_F}{\sigma_S}$$

Solving for $E[R_S]$, we get:

$$E[R_S] = R_F + \frac{E[R_M] - R_F}{\sigma_M}\, \sigma_S \tag{3.18}$$

Equation (3.18) suggests a relation between the expected rate of return and risk of any efficient portfolio (S). The second component of the right side indicates the risk premium an investor requires to invest his money on portfolio S.

3.2.3 Capital Asset Pricing Model

Equation (3.18), fails to describe equilibrium returns on non-efficient portfolios and securities. This problem was solved by another model of Capital Market Theory called Capital Asset Pricing Model (CAPM). CAPM was a seminal work of Treynor (1961, 1962) and introduced by Sharpe (1964) but Lintner (1965a, b) and Mossin (1966) also contributed to the configuration of its final form. Black (1972) also developed a zero-beta version of this model. Following there is a brief presentation of the standard form of CAPM.

The wisdom is, when a portfolio is well-diversified, non-systematic risk tends to eliminate and the risk associated to the portfolio is only systematic. Moreover, given the assumptions of Capital Market Theory, all investors are expected to hold the market portfolio which is well-diversified. Recall that, given the assumptions, investors only concern about the expected return and risk. Since all investors hold well-diversified portfolios beta is the correct measure of risk and hence this model lies on the space of expected return and beta instead of expected return and standard deviation presented in CML.

Figure 3.2

This line graph presents the *Security Market Line* (SML). Vertical axis is related to expected portfolio returns and horizontal axis is the portfolio beta. Market portfolio (spot M) is the portfolio of all assets. The highest the value of beta the more exposure to market risk is inherent to a portfolio. The riskless asset (which offers returns equal to R_F) has no risk at all and thus has a beta equal to zero.

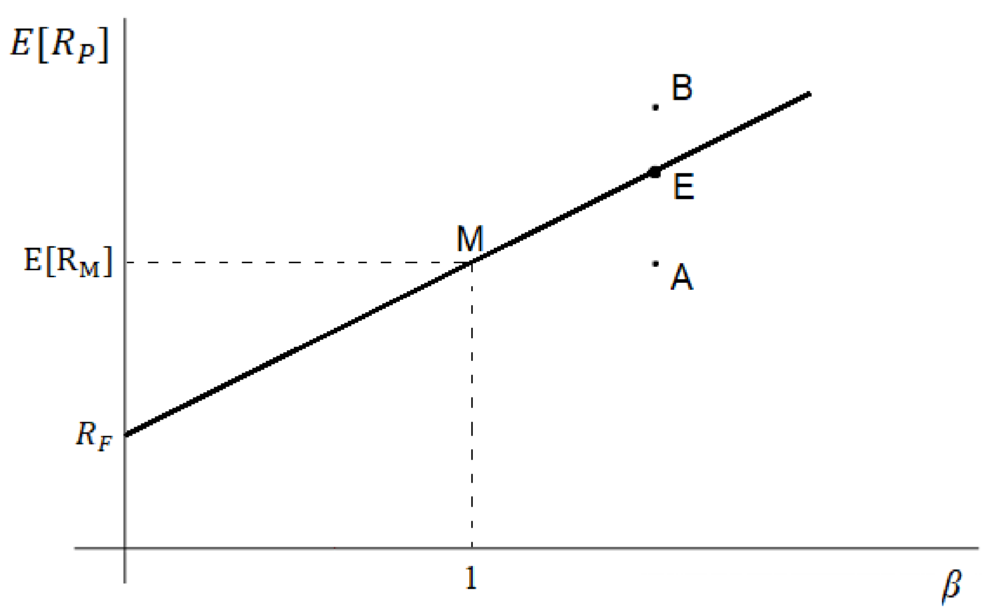


Figure 3.2 presents the *Security Market Line* (SML), a line which contains all potential securities or portfolios investors would choose and presents a relationship between the expected returns of any security or portfolio of assets and its systematic risk. Vertical axis gives the expected rates of return, whilst the horizontal one gives each portfolio beta. A portfolio beta is the sum product of each individual security beta times its proportion invested. An individual security's or portfolio's beta is given by equation:

$$\beta_i = \frac{Cov(R_i, R_M)}{\sigma_M^2} \tag{3.19}$$

where, i is a security or a portfolio regardless its efficiency.

Notably, point M represents the Market Portfolio as presented in CML and contains all the assets in the world. Beta measures the sensitivity of a security or portfolio to the changes of market. Hence, when referring to the market portfolio, its beta equals 1 since it is sensitive to its own changes in value. Using the mathematical approach, (3.19) gives:

$$\beta_M = \frac{Cov(R_M, R_M)}{\sigma_M^2} = \frac{\sigma_M^2}{\sigma_M^2} = 1$$

The linear SML crosses points R_F and M and its slope is positive.

By using the SML, we derive a linear relation between the expected rate of return of any security or portfolio, i, and its risk which is:

$$E[R_i] = R_F + (E[R_M] + R_F)b_i \tag{3.20}$$

Formula (3.20) is the basic form of CAPM and uses the market portfolio as benchmark to extract this linear relationship. In particular, comparing (3.20) with (3.18), CAPM is a more general equilibrium model since it responds to any individual security or portfolio (whether it is efficient or not). Recall that in CML analysis, the relation is valid only when efficient portfolios are examined. Formula (3.20) is decomposed into two parts. The first component on the right-hand side is the time value and the second part is the risk premium an investor requires to hold i security or portfolio. On the same graph, portfolios A and B could not exist with these characteristics of expected returns and risks for the long-run. If there is a portfolio A with expected returns higher than the portfolio's E respectively, offering the same risk level, investors would buy A and sell E achieving risk-free profits. The mass demand of A would increase its price and hence its expected returns would decrease to match E's expected returns. Similarly, if a portfolio B exists with expected rate of return lower than $E[R_E]$ carrying the same risk level β_E, arbitrageurs would exploit risk-free profits by selling B and simultaneously buying E. This action would adjust the expected rate of return of B since it is assumed that no mispricing in markets could take place. Thus, A and B would end up having the same characteristics with E and spotted on the SML. Another important observation is, when a portfolio is efficient, from (3.18) and (3.20) we get that:

$$\beta_s = \frac{\sigma_s}{\sigma_M}$$

which is compatible with saying that the correlation of the expected returns of any efficient portfolio with the expected returns of the market portfolio equals 1.

Comparing the standard form of CAPM with the CML model, both models give a linear relation between the expected return and risk. CML's basic equation however is valid only to efficient portfolios whereas CAPM seems an appropriate model to use on any security or portfolio as well. CML uses the standard deviation as a measure of risk whilst CAPM finds appropriate to use the beta coefficient. Finally, CML is an efficient frontier of portfolios as opposed to CAPM which is an equilibrium relationship in the capital markets.

Although its simplicity of use, CAPM has its drawbacks. Obviously, this model is based on very restrictive assumptions. Another problem is, despite the backward-looking of expected returns on any asset, one could fail to derive reliable estimations of future returns in case where additional factors influence returns. In addition, the market portfolio cannot be recognized as Richard Roll (1977) argues. Indeed, the market portfolio contains all assets in the economy and thus it is impossible to evaluate it since its returns is the wealth-weighted sum of the returns of all assets. Unfortunately, researchers who attempted to examine the validation of this model, had implicitly assumed efficient market indices as a benchmark without any preliminary test of the index efficiency.

3.3 Arbitrage Pricing Theory

An alternative approach in determining asset prices in equilibrium with arbitrage arguments was developed by Stephen A. Ross (1976). This approach is based on the law of one price, meaning that two assets with the same characteristics cannot differ in prices and on the law of large numbers where investors can succeed a complete diversification on their portfolios and is called Arbitrage Pricing Theory (henceforth APT).

3.3.1 Definition of Arbitrage

Arbitrage is referred to the chance one has, to make risk-free profits by exploiting any security mispricing. To succeed it, a simultaneous purchase and sale of securities with the same characteristics is required. For example, if a security was sold in two markets for different prices, one could profit from this discrepancy by purchasing the security in the market offered in lower price and simultaneously selling it to the market where its price is higher. This would allow an investor (called arbitrageur in that case) to earn profits without undertaking risks, or better without requiring to invest an initial amount of his/her own money. An assumption under which, there is no arbitrage in the market is not necessarily a restrictive one. From a perspective, if an arbitrage opportunity arises, assuming at least few investors are well informed, this opportunity would not exist in the long-run as they would detect the price discrepancies and see the benefit to buy from the cheap market and sell to the expensive one. The critical point is, in case where an arbitrage portfolio[1] exists, investors would be satisfied by holding an infinite position on it. The mass demand in the cheap market would cause the price to bid up and the mass offering in the expensive market would decrease the price so as to adjust those market prices to a single price, the fair one. We could argue that arbitrageurs help in that way for the price discrepancies in tradable assets to disappear. In the real economy arbitrage opportunities are difficult to become recognizable, especially in capital markets. One more reason why they cannot be exploited is the existence of transaction costs. Even if such an opportunity has been recognized, transaction costs often make it costly.

Under the assumptions of Capital Market Theory, we concluded that the market is in equilibrium. In the theory of Arbitrage Pricing, if the security prices allow for arbitrage, it is expected that arbitrageurs will pressure the markets to adjust their prices (i.e. to correct them) and restore equilibrium. Thus, it is the arbitrageurs that by rule do not allow for risk-less profits. Otherwise they would exploit these opportunities in an extent that asset prices would adjust to their fair prices.

[1] An Arbitrage Portfolio requires a zero investment and is not exposed to any risk at all.

3.3.2 Development of the Theory

APT is a more general model than CAPM and states that asset pricing can be affected by more than one influences. Its implementation requires no such restrictive assumptions as in the case of CAPM. Specifically, three essential assumptions are needed on this approach. These are:

A1. No arbitrage opportunity exists in capital markets, or arbitrage opportunities are exploited by investors immediately since capital markets are perfectly competitive and frictionless. The no-arbitrage argument has been extensively used in the literature since it is an acceptable one and describes well the market equilibrium. The term frictionless implies that there are no transaction costs or taxes, and there are no limits of short selling the assets.

A2. Investors seek to maximize their wealth, that is, they always prefer more to less wealth.

A3. There is a (known) process generating security returns and investors use the model of this process to make (homogeneous) expectations about the random returns. To avoid any ambiguity, investors are not required to have identical anticipations about the whole model, but they are only assumed to make identical expectations about the ex-ante returns.

Two conditions are also needed for this theory:

C1. There are enough securities in the market, so that a well-diversified portfolio can be constructed.

C2. There are enough securities in the market, so that a portfolio can be constructed with zero investment and no risk at all.

The first condition (***C1***) is based on the law of large numbers imposing an almost infinite number of assets, but is not a restrictive one as investors, by and large, can diversify their portfolios. The second condition (***C2***) implies short-selling is allowed and is not costly. In this case investors can easily short-sell stocks and raise funds to buy stocks. Hence, they can construct a portfolio of stocks with negative (due to short-sold stocks) and positive (due to long position on stocks) weights, with the sum of weights equals to zero.

Under the third assumption (***A3***), the returns on any security (at any time period t) can be described linearly by a set of factors as:

$$\tilde{R}_{it} = a_i + b_{i1}\tilde{F}_{1t} + b_{i2}\tilde{F}_{2t} + \cdots + b_{ik}\tilde{F}_{kt} + \tilde{\varepsilon}_{it} \tag{3.21}$$

where,
$\tilde{R}_{it}$ is the actual rate of return of stock i, $i = 1,2, \dots, n$
a_i is a constant
$\tilde{F}_{jt}$ is a common stochastic variable which influences securities returns,

b_{ij} measures the sensitivity of stock i's returns to changes in the value of $\tilde{F}_{jt}$
$\tilde{\varepsilon}_{it}$ is a disturbance term with mean equal to zero and constant variance for each stock.

An additional assumption that n is much greater than k is imposed for algebra purposes in the derivation of the basic APT equation. Ross (1976) also assumes that the aggregate demand of each asset is positive meaning that investors wish to hold the assets that market offers and their expectations about returns are uniformly bounded to prove his theory. Consider a process generating returns as presented in (3.21). At any time, *t*, the expected value of (3.21) is:

$$\bar{R}_{it} = a_i + b_{i1}\,\bar{F}_{1t} + \; b_{i2}\,\bar{F}_{2t} + \cdots + \; b_{ik}\,\bar{F}_{kt} \qquad (3.22)$$

Subtracting (3.22) from (3.21), we have:

$$\tilde{R}_{it} - \bar{R}_{it} = b_{i1}\,(\tilde{F}_{1t} - \bar{F}_1) + b_{i2}\,(\tilde{F}_{2t} - \bar{F}_2) + \cdots + b_{ik}\,(\tilde{F}_{kt} - \bar{F}_k) \; + \tilde{\varepsilon}_i$$

and letting $\tilde{f}_{jt} \triangleq \tilde{F}_{jt} - \bar{F}_j$, then the ***return generating process*** is:

$$\boldsymbol{\tilde{R}_{it} = \bar{R}_{it} + \sum_{j=1}^{k} b_{ij}\,\tilde{f}_{jt} + \tilde{\varepsilon}_i} \qquad (3.23)$$

where,

$\tilde{R}_{it}$ denotes the actual returns on stock *i* at the end of period t,
$\bar{R}_{it}$ is the expected returns on stock *i*, at the beginning of period t,
$\tilde{f}_{jt}$ is the jth (common) factor realization at the end of period t,
b_{i1} measures the sensitivity of stock i's returns on the common factor $\tilde{f}_j$, and
$\tilde{\varepsilon}_i$ is the idiosyncratic effects on stock *i*'s returns.

The process presented in formula (3.23) is reliable if the following conditions hold true:

i. The expected value of the common factors and the idiosyncratic factor is zero. That is:
$$E\big[\tilde{f}_j\big] = E[\tilde{\varepsilon}_i] = 0$$
ii. The noise term of each stock's return has an expected value of zero conditional to the factors:
$$E\big[\tilde{\varepsilon}_i|\tilde{f}_j\big] = 0$$
iii. There is no severe autocorrelation between the error terms of any pairwise of stocks:
$$E[\tilde{\varepsilon}_i\;\tilde{\varepsilon}_s] \approx 0, \qquad \forall\; i \neq s$$
Notice that if the co-movement between the $e_i{}'s$ is strong, this means there are more than k common factors influencing the returns.
iv. The error term of each stock is uncorrelated with any pervasive factor:
$$E\big[\tilde{\varepsilon}_i\;\tilde{f}_j\big] = 0 \quad \forall\; i\; and\; j$$
v. The factor realizations and the disturbance term do not expose serial correlations upon time:

$$E\left[\tilde{f}_{jt}\,\tilde{f}_{j\tau}\right] = E[\tilde{\varepsilon}_{it}\,\tilde{\varepsilon}_{i\tau}] = 0 \quad \forall\, t \neq \tau$$

As of now, we will present the above stochastic variables without the tilde (~). The factor realizations (f_j's) are mean zero. Otherwise their expected value would be absorbed in the value of $\bar{F}_j's$ and hence would influence the expected returns ($\bar{R}_i$). To give an economic interpretation, if the expected values of these realizations were not zero, investors would consider its expected values when forming their expectations about securities returns, and thus should affect the intercept ($\bar{R}_{it}$) of (3.23). This indicates that the value of f_j's causes a variation on securities returns. Put it another way, the factor realizations (f_j's) measure the unanticipated changes of the independent common variables which determine the realized returns of a security. To get an idea of what these common factors represent, we may think about macroeconomic variables such interest rates or the GDP and Indices in Stock Exchange market. We may observe from (3.23) that the beta coefficients are unique to stock i, but the value of each factor f_j for any j=1, 2, …, k is common to any stock. For example, if GDP is considered as a macro-variable affecting securities returns (i.e. F_{GDP} in (3.21)), then f_{GDP} measures the *unanticipated* change of GDP and b_{iGDP} is the sensitivity of security i returns to this movement. The error term contains all the other factors affecting specifically the certain stock and not commonly all stocks in the market. For this reason, the error term is referred as *idiosyncratic shocks*, or *firm-specific events* and is diversifiable. Hence, a factor affects all stocks or at least a large group of stocks but not at the same volume, whilst ε_i contains factors affecting specifically security i's returns or at most a minority group of securities. Idiosyncratic shocks are also mean zeros. Otherwise, under the same arguments they would affect the intercept. Notice that this condition holds both econometrically and economically. Their expected value of zero conditional to the factor realizations (see Condition (*ii*)) also must hold. Otherwise, if common factors had a systematic effect on the disturbance terms, the latter would no longer be specific to the firms. Given the Condition (*iii*), it is not wrong to expect a co-movement of ε_i and ε_s at any time t if securities i and s are referred to firms with similar firm characteristics (i.e. participating in the same industry) because certain types of risks may arise in industrial level. The presence of severe across-firms correlation of error terms though, would mean additional common factor/ or factors exist that is not presented in the model. Burmeister, Roll and Ross (1994) remark «***the risk factors themselves may be correlated …***». Indeed, considering inflation and interest rates as potential factors for instance, one is related to another. Though these variables should not be regarded as legitimate APT factors because they are partially predictable, unanticipated inflation and unexpected movements of interest rates could be tested as legitimate APT factors. Berry, Burmeister and McElroy (1988) discuss these differences and point out three properties a legitimate APT factor must have:

1. At the beginning of the period, the factor must be unpredictable. This statement fits to the (*i*) and (*v*) conditions quoted above.
2. The factor must have a pervasive influence on stock returns.
3. It must influence expected returns, meaning it is a priced factor. We may discuss this property extensively when we derive the basic APT equation.

Now, consider an investor holds a well-diversified portfolio, p, with n securities, where n is sufficiently large and *equal* investments on each security. Under the first condition (***C1***) he/she succeeds to eliminate the idiosyncratic risk of the portfolio:

$$\varepsilon_\rho = \sum_{i=1}^{n} x_i\, \varepsilon_i = \frac{1}{n}\sum_{i=1}^{n} \varepsilon_i \approx 0 \quad \text{when } n \to \infty \tag{3.24}$$

Ross (1976) had assumed an economy with infinite number of securities, and hence the approximation of (3.24) could be applied[2]. However, Dybvig (1983) derived the theory in a finite economy giving an explicit bound on the deviations from the pricing suggested in APT and found these deviations to be negligible. If the second condition (***C2***) holds true, a portfolio with the following characteristics can be formed:

$$\sum_{i=1}^{n} x_i = 0 \tag{3.25}$$

$$b_{pk} = \sum_{i=1}^{n} x_i b_{ij} = 0 \qquad \forall\, j = 1,2, \dots, K \tag{3.26}$$

Equation (3.25) states that the sum of proportions invested in each security equals zero, or better, no initial investment is required for this portfolio. Hence, the purchases of some assets must be financed by sales of others. Formula (3.26), implies that the portfolio is not exposed to any systematic risk. Since the portfolio requires no investment and is not exposed to any risk, systematic or idiosyncratic, based on the first assumption (***A1***) its expected return should strictly equal to zero:

$$\bar{R}_p = \sum_{i=1}^{n} x_i \bar{R}_i = 0 \tag{3.27}$$

The economic interpretation of (3.27) is, if the equation was violated, then arbitrage opportunities would arise, and thus investors would exploit the chance to make potential profits without requiring funds and without being exposed to any risk due to short-sold stocks. Using algebra to approach (3.27), equation (3.25) implies an x vector of investment proportions (i.e. weights invested on each asset) is orthogonal to a vector of ones, say $\epsilon = \langle 1, \dots, 1\rangle$, while (3.26) implies the same vector to be orthogonal to the *k* vectors b_{ij} where j is related to the jth factor. If a vector is orthogonal to N-1 vectors, and this condition implies that it is also orthogonal to the Nth vector then the Nth vector can be expressed as a linear combination of the N-1 vectors. Figure 3.3 depicts the geometric argument of these orthogonal (perpendicular) vectors. This linear combination would give:

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[2] Arguments are similar to equation (2.18) and the general discussion of subsection 2.4: «Benefits of Diversification».

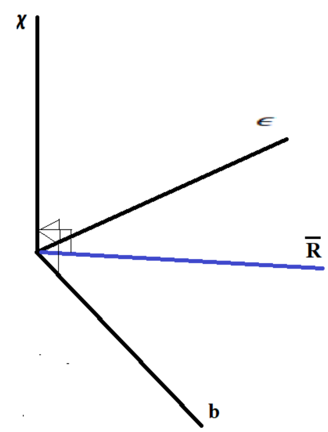
$$\boldsymbol{\bar{R}_i = \lambda_0 + \lambda_1 b_{i1} + \lambda_2 b_{i2} + \cdots + \lambda_k b_{ik}} \tag{3.28}$$

where,

$\bar{R}_i$ is the expected rate of return of any security or portfolio i,
λ_0, λ_1, …,λ_k are the prices of risk which remain constant cross-sectionally and
b_{i1}, b_{i2},…, b_{ik} measure the sensitivity of security i to the relevant factors f_1, f_2,…,f_k and are called *betas* or *factor loadings* (in terms of factor analysis).

Figure 3.3

The following figure reveals the geometric interpretation of the non-arbitrage arguments. Axis χ denotes a vector of portions invested on different assets (weights). Vector ϵ is simply a vector of ones. $\bar{R}$ is a vector of securities' expected returns and b represents exposures to systematic risks.



Formula (3.28) gives the *general equation of Arbitrage Pricing Theory* and should be applied to any security or portfolio in equilibrium when their returns are generated by a multifactor model as described above in (3.23). The product $\lambda_1 b_{ij}$ is the contribution in total returns of i when the returns are exposed to a risk generated by the factor f_j. In order to find the parameters λ_0, λ_1, …,λ_k the following procedure is necessary. We form k+1 well diversified portfolios, where each one has the following *particular* characteristics:

1st portfolio: b_{p1} = 1, b_{p2} = 0, b_{p3} = 0, …, b_{pk} = 0

2nd portfolio: b_{p1} = 0, b_{p2} = 1, b_{p3} = 0, …, b_{pk} = 0

3rd portfolio: b_{p1} = 0, b_{p2} = 0, b_{p3} = 1, …, b_{pk} = 0

and work at the same manner until,

kth portfolio: b_{p1} = 0, b_{p2} = 0, b_{p3} = 0, …, b_{pk} = 1

and finally, a zero-beta portfolio: b_{p1} = 0, b_{p2} = 0, b_{p3} = 0, …, b_{pk} = 0

By substituting the betas of (3.28) with the betas of the zero-beta portfolio we get $\bar{R}_z = \lambda_0$. Subsequently, allowing betas of the first portfolio to generate the expected returns of (3.28), we get:

$$\bar{R}_1 = \lambda_0 + \lambda_1 \rightarrow \lambda_1 = \bar{R}_1 - \lambda_0$$

On the same manner, considering all portfolios we derive the following equation:

$$\bar{R}_i = \lambda_0 + b_{i1}(\bar{R}_1 - \lambda_0) + b_{i2}(\bar{R}_2 - \lambda_0) + \cdots + b_{ik}(\bar{R}_k - \lambda_0) \qquad (3.29)$$

and if there is a tradeable asset in the market that is free of risk then, with the no-arbitrage arguments the returns on the zero-beta portfolio should be identical to the risk-free rate of return, meaning that $\bar{R}_z = \lambda_0 = R_f$. If we impose the assumption of the existence of such a riskless asset, then we can transform (3.29) to:

$$\bar{R}_i = R_f + b_{i1}(\bar{R}_1 - R_f) + b_{i2}(\bar{R}_2 - R_f) + \cdots + b_{ik}(\bar{R}_k - R_f) \qquad (3.30)$$

From (3.28) we have finally produced the formula (3.29) of which brief description is the following. The expected returns of any security or portfolio of securities in equilibrium is equal to the risk-free rate of return (or the common return of zero-beta portfolios in case where the riskless asset does not exist) plus the sum product of the prices of risk of any j factor and the factor sensitivities. This is equal to saying that the excess expected returns on each security or portfolio are described by the risk premia of the pervasive factors. It is more convenient to consider the λs as prices and b_{ij}'s as quantities, where their product gives a value. The analysis described above implies there is no reason for pricing any firm-specific risk factor since risks identical to assets' characteristics could be diversified by investors and hence, they should not be rewarded for bearing such risks. Similar to CAPM, equation (3.29) states that investors require compensations due to the time value of money (R_f) as well as the risks they undertake by investing in risky assets (premia of which is given by the sum product of the right-hand side).

Roll and Ross (1980) state that «***any well-diversified portfolio could serve the same function and that, in general, k well-diversified portfolios could be found that approximate the k factors better than any single market index***». They also argue that, since the market portfolio is expected to bear not much idiosyncratic risk, it could be used to substitute one of the above factors, but in contrast to the CAPM, it is not necessary to include all of the available assets of universe to the portfolio as the APT can be tested by examining only subsets of the set of all assets. Elton and Gruber (1995) acknowledge that the $b_{ij}'s$ are either the respective sensitivities of the returns of security i to the risks generated by the common factors or are unique characteristics of a security i such the dividend yield for example. Specifically, comparing two assets, say A and B, which are affected by unexpected movements of the value of a factor called j, if A is highly exposed to the certain risk whilst B is slightly exposed, the b_{Aj} will be greater than b_{Bj} and the latter will be close to zero. If a security, say i, has $b_{ij} = 0$, this means it is not exposed to the certain type of risk caused by f_j, and thus, its returns will not be affected to any value of f_j. The price of this risk λ_j, should not change cross-sectionally, albeit it can vary over time, as well as the factors affecting stock returns may change on different time periods. The APT's permission of changing risk premia and the nature of the factors upon time, reveals one of the difficulties in determining common factors in an APT framework. It is easy to conclude through a glance at (3.28) and (3.29) that the risk premia are typically, the extra expected returns required from investors who are interested in security i because of its sensitivity to the common factors. Obviously, only these factors are priced, and the idiosyncratic components of risk should not have an effect on the expected returns. There are cases though, where certain common factors are not priced by the markets, but they affect assets' returns.

3.3.3 Critical Differences between APT and CAPM

Both theories have derived a relationship of expected returns and risk in securities and portfolios of which prices are in equilibrium. CAPM relies on risk-return dominance argument to support equilibrium prices. Based on this argument, when the equilibrium prices are violated, investors will adjust their portfolios by seeking underpriced securities and drawing away overpriced securities, since it is assumed that they want to maximize their expected returns on a certain level of risk. The extent of each investor's portfolio adjustment depends on their risk-aversion degree. This argument states that the aggregation of these limited changes results in a large volume of biding and offering prices and implies that many investors are well informed to make these adjustments. Instead, APT relies on the no-arbitrage condition to support equilibrium prices. Based on this argument, when an arbitrage opportunity arises, an informed investor desires as large position as possible to earn as many risk-free profits he/she can. Therefore, just a few investors are enough to correct the prices, assuming they have identified the mispricing. CAPM's argument of a large number of mean-variance optimizer investors is hence more critical than APT's argument where only a few investors can restore equilibrium.

Consequently, a model such that proposed by CAPM bases its arguments on utility theory whereas APT does not require such an assumption. On the other hand, APT derives its relation by a process which generates security returns. Of course, in case where APT is valid, does not necessarily mean that any other theory should be rejected. Many argue that APT is a precursor and a general form of CAPM. Even if both models are valid, the multifactorial character of APT surpasses the standard form of CAPM insofar as it allows for better descriptions of returns. For example, if the return generating process includes two common factors, namely industrial production and interest rates, then we would expect investors would take advantage of acquiring information such how much a certain security is exposed to risks inherent in aggregate industrial production and interest rate movements. Such types of information allow for better hedging techniques.

It is noteworthy that APT does not require a riskless asset that is tradeable and offers a risk-free rate. In the standard form of CAPM, investors could lend (borrow) unlimited amounts of a riskless asset. Black (1972) however has proposed a special case of CAPM where investors are not allowed to lend on riskless securities and a case where the riskless asset does not exist at all. This is known as the zero-beta form of CAPM.

A remarkable weakness of APT is that the common factors have not been identified by theory. Since we do not know their identity and the exact number of the priced risks as well, it is extremely hard to put this theory into practice. The standard form of CAPM is an appealing model because the single factor has been defined and its price of risk is the excess return of the market portfolio. Theoretically, any investor could estimate this price if the market portfolio was recognized. Hence, both models cannot be used adequately to estimate the ex-ante returns of a security or a portfolio due to the undefined factors for the first case and the difficulty to find an appropriate proxy of the market portfolio for the second case. On this spirit, a different approach to develop a testable empirical model has been used extensively in the literature with the provision of multifactor models that capture the essence of APT. This approach allows the researchers to test the influence of certain pre-specified factors (i.e. macroeconomic or financial variables) to a sample of securities or portfolio returns. More about these multifactor models are presented in the following section.

In the literature there is a confusion about the theory behind a variety of multifactor models. In many cases authors claim to have found common factors and thus derived multifactor models consistent with Ross's (1976) APT, whilst others support their models are compatible with Merton's (1973) Intertemporal Capital Asset Pricing Model (ICAPM). The ICAPM suggests that wealth and state variables forecast securities returns. These state variables affect investors' maximization of utility functions (i.e. current wealth). Both APT and ICAPM conclude to very similar models that describe securities' excess returns as a linear function of common risks. In addition, ICAPM does not determine what these state variables are, same as APT about the common factors. Based on Cochrane (2001), in an APT model, R^2 of time series regressions of stock returns on the factors is usually higher than in an ICAPM model. APT's factors are assumed to represent portions of the covariance matrix of securities returns, an assumption not imposed in ICAPM. Although he recognizes that on practice deriving a model from the perspective of law of one price or from the marginal utility aspect does not have a severe impact, he claims that APT analyses start from the covariance matrix of returns whilst ICAPM from the recognition of variables that could potentially affect the conditional distribution of future returns. Based on Cochrane (2001), models such of Chen et al.'s (1986) seem more like macroeconomic or ICAPM models rather than APT models defined in their paper. On the opposite he recognizes Fama and French's (1993) three factor model as an APT model rather than an ICAPM, due to the fact that their factors are returns on specific portfolios and due to the high r-squared values as well. Maio and Clara (2012), however, have found that Fama and French's (1993) model meets the restrictions imposed from ICAPM. They provide evidence that other studies who claim to test ICAPM, their models are in fact far from this theory.

Even though the distinction of APT models from ICAPM is often invisible, in this study we construct and test a multifactor model which seems compatible with APT. We do not, of course, test the theory of arbitrage pricing due to the fact that no theory specifies the unknown factors. Empirical findings in favor of APT do not necessarily imply another theory should be rejected, but if the factors are also compatible with ICAPM is another story, not examined here.

Section 4. «Literature Survey»

What have we seen so far is the origin and development of the theory. In this section we present and discuss alternative approaches on testing the validity of APT along with empirical assessments concerning the APT. The first attempts to validate the APT were made with statistical analytic tools (i.e. Factor Analysis). In 1986 however, the first effort to assess the validity of the theory by using macroeconomic variables was made, in an attempt to approach the identity of these unknown factors. This effort owes to Chen, Roll and Ross (1986) who inspired many other authors in using multifactor models to explain securities returns. Other attempts have also been proposed such using mimicking portfolios as proxies for the factors (i.e. see Fama and French), which are more or less, connected with this theory.

4.1 Testing the Validity of APT

To test if APT is an appropriate model, one has to test equation (3.28) which is the fundamental result of this theory. However, regressing (3.28) requires the $b_{ij}'s$ to have been estimated a priori. A large majority of researchers dealt with the determination of $f_j's$ of the return generating process (3.23) aiming to identify these $b_{ij}'s$. As already mentioned, the main problem in implementing APT is the lack of determining factors by theory. Bearing this problem in mind, three alternative methods have been used so far in the literature to estimate the $b_{ij}'s$. The first and most widely used method includes statistical techniques like factor analysis or principal component analysis to estimate simultaneously both the factors $f_j's$ and the factor loadings $b_{ij}'s$. A second method includes the specification of factors as a first step followed by the estimation of betas. There are two approaches for this procedure. The first approach supposes a set of macroeconomic variables as the potential factors of APT whilst the second requires the construction of portfolios as proxies for the factors. Specifically, each of these portfolios should be exposed to only one type of risk, that is each portfolio should capture a different type of risk. Whichever approach is followed, the $f_j's$ are used in equation (3.23) as the independent variables to estimate the $b_{ij}'s$ which in sequence are putted into (3.28) to get the prices of risk, $\lambda_j's$. A third method is to pre-specify a set of characteristics identical to each firm as the $b_{ij}'s$ and then regress (3.28) to find the prices of risk. It is important to mention however that the last two methods are joint tests, in the essence that one tests both the validity of APT and the relevancy of the estimators and its coefficients (Gruber & Elton, 1995).

4.2 Use of Statistical Techniques

4.2.1 Statistical Factor Models

There are several statistical techniques used to identify the pervasive factors affecting securities returns and the sensitivities of each security to these factors, where factor analysis and principal component analysis have been dominant. Both techniques produce simultaneously these sensitivities (the factor loadings) and the factors.

Given a set of securities' returns over a specified period, Factor Analysis (FA) explores factors affecting the co-movement of these returns. Hence, this technique extracts the factors through the covariance matrix of returns. The procedure starts when putting in an arbitrary number that we believe is the correct number of factors, say k. Factor analysis then finds contemporaneously these k factors and the factor loadings of every security returns to each of these k factors in a fashion that tries to eliminate the covariance of residual returns[3]. There are many methods to derive the results such the *Generalized Least Squares* and the *Unweighted Least Squares*, but the most widely used is the *Maximum Likelihood*. The derived factors need not necessarily be orthogonal and are simply a weighted average of the securities returns. Apparently, each factor has different weights. It is common to perform this analysis on the same data set with different prespecified number of factors each time (say k, k+1, k+2) and compare these results to estimate what number seems to be more appropriate. But answering the question when one should stop adding factors, is a rather subjective matter. An analyst should stop increasing the number of factors when the probability that an additional factor is needed drops below some (subjectively chosen) level.

Principal Component Analysis (PCA), given a set of securities' returns over a time period, explores the pervasive factors through analyzing the variance-covariance matrix of these returns. At first, an index (which is a weighted average of the securities) is constructed so as to explain as much as possible the variation of the securities' returns. In sequence, for the unexplained portion of the variance-covariance matrix a second index will be constructed with the restriction that the second index has to be orthogonal, which means that the two indices are uncorrelated to each other, and this procedure ends when it is estimated that the additional index explains more of random influences rather than real information[4]. These indices are called principal components and are simply statistical estimations of the common factors affecting the sample of securities returns without requiring naming these factors.

Regardless of the statistical technique used to derive the $f_j s$ and the $b_{ij} s$ to test the APT a cross-sectional test is needed, in turn for each period, to estimate the prices of risk, λ_js. Having computed these prices for each period we are then able to obtain their average values and their variance.

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[3] With the term "residual returns" we refer to the portion of securities returns that is not influenced by these factors.
[4] In PCA, when additional indices are extracted, the random noise in the unexplained portion of the variance-covariance matrix increases and therefore each successive index is more possible to contain random movements.

4.2.2 Empirical Tests using Factor Analytic Techniques

The first empirical work related to APT was made by Gehr (1975) who used 24 industry indices and 41 individual stocks with 30 years of data in the USA. The method he used is *principal axis extraction* and found at least two and probably three factors affecting the stock market in common. These factors were not predominant in explaining the sample stock return variances, though they explained a large proportion of them.

After half a decade, Roll and Ross (1980) extended the idea of Gehr and tested the APT in a more comprehensive way. They used a two-step procedure involving the estimation of expected returns and factor loadings from time series data on individual asset returns and then performing cross-sectional regressions on the basic APT equation. To test the theory, they used a sample of data from 1,260 securities listed on the New York or American Exchanges and separated the returns of securities into 42 groups of 30 securities each, by alphabetical order. They selected the daily returns of those securities from 3 July 1962 to 31 December 1972. To estimate the number of factors and the factor loadings, on the first step procedure, they applied the *maximum likelihood* method of Factor Analysis. On the second step procedure they investigated the existence of significant prices of risk. By testing the basic hypothesis that there exist non-zero constants (λ_0, λ_1, …, λ_κ) when running cross-sectional regressions of the basic form of APT against an unspecified alternative hypothesis they found at least 3 but no more than 4 factors significant when λ_0 was arbitrarily set to be 6% and 2 significant factors when λ_0 was estimated on regression. Against the alternative hypothesis that other non-diversifiable variables are priced, such the "own" variance of individual assets returns they found this variable to have significant explanatory power but the source of this spurious effect was the skewness. Applying a procedure to resolve this problem, they finally concluded that only 9 out of 42 groups displayed significant standard deviations. Finally, since one problem that arises in factor analysis is that factors cannot be identified and hence one cannot make comparisons across different groups and since the results could contain spurious sampling dependence among the groups, Roll and Ross tested the only parameter which should not differ significantly across different groups (regardless the sample rotation of the factors), the constant λ_0, and found no evidence of different intercept terms across the groups.

An investigation to determine whether the APT can explain differences in returns caused by the firm size effect was implemented by Reinganum (1981). Reinganum's work is lying in two stages. On the first stage, having estimated each securities' factor loadings in year Y-1 and then grouped securities with the same factor loadings into control portfolios, excess securities returns are computed in year Y. These excess returns are calculated by subtracting the daily control portfolio returns from the daily security returns. On the second stage, securities are sorted by their market value of their common stock in year Y-1, and 10 "market value" portfolios with equal weights are constructed for the year Y. For example, the excess returns of the bottom 10% securities (of firms with the smallest market values) are combined to calculate the excess returns of the first market value portfolio (MV1) in year Y. Similarly, the excess portfolio returns for the year Y are computed for all the other 9 portfolios, with MV10 being the portfolio consisted of the top decile securities (which they had the highest market values in year Y-1).

The null hypothesis Reinganum tests is that the 10 market value portfolios have zero average excess returns. If it is rejected, is an evidence that the APT cannot explain an empirical “anomaly” of CAPM. The sample consisted of stocks trading on the NYSE and ASE, with daily returns data. The number of sample stocks varied each year from 1,457 to over 2,500 for the period between 1963 and 1978. Since the procedure to estimate each securities’ factor loadings for all this data is extremely hard and requires the decomposition of a NxN covariance matrix with N be the number of stocks tested, Reinganum employed a method suggested by Chen (1980)[5]. Therefore, in each year Reinganum constructed 30 random portfolios to estimate their factor loadings via factor analysis and then estimated the factor loadings of individual securities by using the covariance between the securities and portfolios returns. The construction of control portfolios as a next step at the first stage relies on the idea that securities with the same factor loadings should have similar average returns. Factor analysis was employed by assuming that the number of factors was 3, 4 and 5 and hence three different tests were implemented.

By completing both stages, results seemed to be inconsistent with what theory expected. For all of the three tests, the average market value portfolio excess returns were not zero. MV1 had a positive and MV10 a negative, both statistically significant, average excess returns. In addition, the small firms experienced approximately a 20% per year greater mean average excess returns than the large firms. Reinganum concludes that the evidence does not support the APT, but the tests do not indicate the source of this failure and hence one should not characterize it as an inadequate model. Since the hypotheses that are violated are not revealed, we should suspect all of them, i.e. the return generating process may not be linear or arbitrage opportunities may have existed in at least one of the examined Stock Exchanges during the testing period.

Chen (1983) attempted to compare the two nonnested alternatives APT and CAPM as well to reject the APT using variables that have had been characterized as empirical “anomalies” in the CAPM. The wisdom is, if variables such the own variance and firm size are significant after the factor loadings are accounted for, the APT should be rejected. Chen used daily returns data from securities listed on NYSE and AMEX for the period 1963-1978 and divided this period into four subperiods (1963-1966, 1967-1970, 1971-1974 and 1975-1978) to have four independent tests of each testable hypothesis. The number of securities varied depending on the subperiod from 1,064 to 1,580.

At first, Chen computed the sample covariance matrix of the first 180 stocks (in alphabetical order) and obtained the first 10 factor loadings for each stock. Next, he formed five portfolios using linear programming in a manner to balance estimation errors with other desirable properties. The time series of these portfolios should contain linear combinations of the factors. At last, he produced the first five factor loadings for each stock in the sample by solving a matrix equation. Chen reasons the number of factors is chosen to be 5 from previous empirical works (see Roll and Ross

[5] Based on this method, if one knows the factor loadings on a group of, say k, securities or portfolios, then the factor loadings for all securities can be estimated if we know the covariance between these securities and the k portfolios.

(1980), Reinganum (1981), Brown and Weinstein (1983)). What is more, to derive the FLs (for APT) and the betas (for CAPM) Chen used the odd days data, whilst for the estimation of returns on the regression lines he used the even days respectively. As a market proxy to derive the CAPM's beta, Chen employed the S&P 500 index, the value-weighted stock index and the equally-weighted stock index.

Comparing the cross-sectional regression of returns on both the FLs and the (CAPM's) beta, Chen found the first FL of each asset to be highly correlated with the beta of CAPM. He also found that most of the FLs ($\hat{b}_{i1}'s$) bear a negative sign which seems to be justified with the negative signs of the estimated risk premiums (λ_1's). He notices however that only for the periods 1963-66 and 1975-78 these risk premiums are of high significance (at .05 level) and this comes to fit with the CAPM's regression. The significance of the other premiums seems to vary over the periods. A Hotelling T^2 test is also implemented with the Null-Hypothesis to be that $\lambda_1=\lambda_2=\lambda_3=\lambda_4=\lambda_5=0$, which is rejected, though this test is weak in general. Stating that by treating both the FLs and the beta as independent variables brings multicollinearity problems, he recognized the distinction of the nonnested alternative models by a method suggested by Davidson and Mackinnon (1981) and found a superiority of APT against the CAPM to explain the expected returns.

In sequence, Chen regressed the residuals found on CAPM on the FLs of the APT equation to test if APT was able to capture any other information about the systematic risk that CAPM could not. He found that in most cases the CAPM was misspecified and the relevant information was picked up by the APT. The inverse regression was also implemented, and the results indicated that «*If the APT is misspecified, whatever it misses is not being picked up by the CAPM betas*». In addition, to estimate whether the own variance affects the securities expected return on the APT, Chen computed each assets' own variance within each subperiod and separated the securities into two groups (portfolios) depending whether their variance is above or below the median. Using a programming technique, he constructed the two portfolios so that they have the same FL. If APT is a correct model, the portfolio returns should not differ significantly. Indeed, the results showed no effect of the own variance net of the FLs, but the difference in returns is not fully accounted for by the FL. Lastly, to test the firm size effect, Chen separated the firms into two categories (large and small) and again two portfolios were formed so as to have the same FL. With a 95% confidence interval, he found only one out of four subperiods to display significant different returns between the two portfolios and therefore concluded that the firm size did not have explanatory effect net of the FL.

Cho, Elton and Gruber (1984) found that Roll and Ross's methodology in grouping stocks had a problem of comparability. Indeed, to compare the results between two or more different groups of stocks, the maximum-likelihood factors should first be tested somehow to see if they are the same and/or in the same order across these groups. They repeated Roll and Ross's procedure with a sample referring to a later period and found more significant factors than those of Roll and Ross. Although this procedure often results in an overestimated number of factors, they confirmed that more factors than the zero-beta CAPM's theory determine equilibrium prices.

In addition, Dhrymes, Friend and Gultekin (1984) applying Roll and Ross's procedure found a positive relationship between the number of securities within the groups tested with factor analytic techniques and the number of significant factors appeared on results. With a 95% confidence interval, they found at most two factors with a group of 15 securities and when the group size was doubled at most three factors were found affecting securities returns. Moreover, with a group of 45 securites at most four factors were found significant and with a group of 60 securities at most six. Lastly, with a larger group size of 90 securities factors increased to nine at most. Dhrymes, Friend and Gultekin (1984) criticized Roll and Ross's methodology as one which is flawed and that individual factors should not be tested whether they are significantly priced. In their sample they found almost similarly that the increment of the group size from 15 to 60 securities raised the number of significant factors from 3 to 7. They argue that the sample division into separate groups brings problems as important sources of the covariance between securities in different groups may be lost and, also, different groups may not necessarily contain the same factors, thus results depend on how the stocks have grouped. Roll and Ross (1984) then replied to the above criticism insisting that testing individual factors for their pricing influence is reasonable despite the rotation problem. They argue that there may be detected many factors but since most of them are diversifiable they should not be priced.

Beenstock and Chan (1986) also used Roll and Ross's methodology for 220 securities in the UK over the period 1961-1981 and found approximately 20 risk factors but point out their results come with the assumption that none of the factors they found is not idiosyncratic. Furthermore, they found securities own variances to be priced which is contrary to the APT, but CAPM was always rejected in favour of APT. Lastly, they provide evidence that by using UK data, similar to US findings, the number of factors is positively related to the sample size.

Connor and Korajczyk (1993) suggested a test for determining the appropriate number of factors when analyzing security returns. Based on their test, assuming a K number of common factors describe well the securities returns, if K+1 common factors have specified on the same data set, then the cross-sectional average of asset-specific variances should not differ significantly from the average of asset-specific variances of the K model since the K+1 factor will be a 'pseudofactor' and will only explain some of the asset variance for a few securities only. If, however, K+1 factors are appropriate, then the average asset-specific variance for the K+1 model should differ from the average variance of the K model. If σ_i is the total variance of security i returns and $\sigma_{\varepsilon i}$ is the portion of total variance not explain by the factors (ie the asset-specific variance) then Connor and Korajczyk (1993) define the explanatory power of the factor model as $1 - (\sigma_\varepsilon \,/\, \sigma)$ where σ_ε and σ are the cross-sectional average asset-specific and total variance of returns respectively. They argue that the explanatory power one additional factor has in a factor model is measured by the change in explanatory power of the model when this factor is added.

4.2.3 A Critique to Statistical Factor Models

Factor analysis was the first tool used to provide an evidence in favor of APT proponents' intuition that more than one factors affect stock markets returns. There are however some problems when statistical techniques are applied. One of the most common problems is the errors-in-variables, where the estimated $b_{ij}s$ contain errors which may affect the significance of the prices of risk for each factor. In addition, there is no meaning to the signs of the $b_{ij}s$ and the f_js since they could be reversed. For example, a negative value of a factor with negative sensitivities of securities returns on this factor would give the same result if they were both positive. Moreover, since the $b_{ij}s$ and the λ_js could be treated such the one could be doubled and the other halved with their multiplication giving the same results, their scaling is rather arbitrary. More importantly though, the identity of each factor is not known and therefore, we are not able to compare the factors between different samples. For example, the first factor extracted from a sample is not necessarily ordered as the first factor in a second sample, or even, it may not appear to influence significantly the returns in the second sample. Another important weakness of the statistical techniques is that the factors are not interpreted theoretically, and this has been extensively criticized in empirical analyses. All these problems along with several concerns raised from the empirical findings (as mentioned above) have implied that other methods are needed to provide further evidence of the existence of more than one risk factors.

4.3 Use of Firm-specific Characteristics

4.3.1 Fundamental Models

Another technique to determine what affects returns is to use fundamental multifactor models. These models use firm-specific characteristics such the dividend yield as the $b_{ij}'s$ to extract factors. In contrast to statistical or macroeconomic factor models, fundamental models do not require time-series regression to extract the $b_{ij}'s$ since the latter are exogenously specified by the firms' attributes. As a result, the derived factors (when regressing returns on these sensitivities) are the realized returns of mimicking portfolios constructed to capture each characteristic. A certain factor represents the realized return per extra unit of the relevant attribute when the other attributes remain constant. Sharpe (1982) tested such a fundamental model. Assuming that equilibrium returns are described by the market beta, the dividend yield, the size of the firm, its sensitivity to long-term bonds, its past value of alpha coefficient (in the CAPM model) and variables depending on eight-sectors, he tested this model on 2,197 stocks for the period between 1931 and 1979 in a monthly basis and found these attributes significantly different from zero for a large portion of total months tested. He also found the adjusted coefficient of determination increased from .037 to .104 comparing the model with all these attributes and the simple CAPM model.

4.3.2 Mimicking Portfolios

Another technique is to form mimicking portfolios according to some characteristics and then estimate the sensitivities of returns to these portfolios. They are called mimicking portfolios as they try to mimic a specific force which is believed to affect stock returns.

A pioneering work using firm characteristics is that of Fama and French (1992a) who find that the beta coefficient of the simple CAPM model has a limited explanatory power and the size and book-to-market equity explain significantly the average stock returns in the US. To capture the latter two attributes, they formed mimicking portfolios. As a proxy for the size factor they set two portfolios one consisting of Small Capitalization securities and one of Large Capitalization securities and differenced their returns (SMB). As a proxy for the value risk factor, they differenced the returns of two portfolios, one consisting of securities with a High Book-to-Market ratio and one consisting of securities with a Low Book-to-Market ratio (HML). Fama and French (1993) also extended their model attempting to explain both equity and bond equilibrium returns. The stock-market factors are the overall market factor and the factors related to firm size and book-to-market equity. The bond-market factors are related to maturity and default risks. Fama and French argue these factors explain good the common variations of returns in the bond and stock markets, as well as the average returns cross-sectionally. In a recent work, Fama and French (2015) extended their three-factor model to a five factor, accounting in addition to the former three stock-market related factors and the profitability and investment factors.

A good question however arises considering why a firm attribute (ie firm size) enters the model in a mediate way? Since these attributes are measured directly within a firm, they could be a sensitivity coefficient alone, such in the case of fundamental models. Answering such a question requires further empirical tests to estimate which approach outperforms one another. It seems valuable to mention though, that the approach used by Fama and French, allows for the investigation of the properties of each attribute both cross-sectionally and by time-series regressions. With the mimicking portfolios approach, one is allowed to test the APT by both the return generating process and by its basic form. A fundamental model however, will only give estimates of the prices of risk (cross-sectionally), but since the sensitivities on each factor has been specified a priori, the return generating process is not taken into account.

4.3.3 A Critique to Fundamental Models

In the literature, many firm-specific characteristics have seen to be related to securities risks. A list of attributes includes the firm size (mainly measured by the market capitalization), growth prospects (i.e. price-to-book ratio), dividend yields etc. There are however some issues of concern. At first, most of these attributes to be measured require data which is sensitive to accounting principles and rules. These rules usually differ across firms making cross-sectional comparisons quite difficult. Another problem is related to the date each firm announces its reports. Hence, the same ratio, for instance, reported from firms may not be appropriate for cross-sectional estimations since different time periods might have been used to its measurement across companies. Another issue is that accounting methods are in most cases backward looking, whilst financial analysis is regarded to be forward looking. Constructing a model which is sensitive to accounting methods should be suspected for its forecasting ability. At last, since there is no established theory, an attempt to explain the risk-return relationship, even with strong empirical indications, might prove to be disastrous if the observed historical relationship between the attributes and stock returns was provisional or spurious. Connor (1995) compared the explanatory power of three types of models (statistical factor, fundamental and macroeconomic) and found the first two outperformed the last one in terms of explanatory power, although he admits ***«…a macroeconomic factor model is probably the strongest…***» in terms of theoretical consistency and intuitive appeal.

4.4 Use of Macroeconomic Variables

4.4.1 Multifactor Models with macroeconomic variables

Another technique which is simpler to apply than statistical techniques because it does not require the mathematical procedure to determine the factors is related to the specification of macroeconomic variables as potential factors. Hence, more series are required as input data than in the case of factor analysis, but they are all observable and their selection is based on financial theory. The first attempt to use a macroeconomic model to test the APT is attributed to Chen, Roll and Ross (1986) who found industrial production, changes in the risk premium and twists in the yield curve to be significant factors along with inflation (a less important factor) in the United States. Their work influenced many other researchers who turned to test the APT in other markets. The reason why a macroeconomic model could be an appropriate model to explain movements in stock prices raises from the observation that stock markets react to shocks occurring in economy[6]. An unexpected event in the economy (i.e. a sudden raise of interest rates from FED to face inflationary pressures) will probably change investors' expectations about future cashflows who will subsequently reform their portfolios. The effect will be more pervasive on stocks of which returns are highly sensitive to interest rate movements. For instance, we would expect companies which hold Government bonds on their portfolios to be exposed on interest rate movements. But it's the unexpected component of this movement which will cause a gap between realized and expected stock returns (as have already explained in subsection (3.3)). On the contrary, the expected part of this movement is considered by investors when they estimate ex-ante returns. Based on the theory of the semi-strong form of efficient market hypothesis (EMH), there's a rapid adjustment of share prices to public announcements. In example, if investors expected an interest rates increment of 0.5% but the Central Bank raised the rates by 2%, the difference of 1.5% is the unexpected part of this increment. Obviously, an accurate decompose of changes in the macroeconomic series into two parts (the expected and the unanticipated part) is not as easy when a researcher analyses ex-post returns but rather a hard challenge to construct an appropriate model.

A large body of research has occupied with using pure macro-economic innovations instead of mimicking portfolios in a pricing model. Among others are, Chan, Chen and Hsieh (1985), Chen, Roll and Ross (1986), Hammao (1988), Berry, Burmeister and McElroy (1988), McElroy and Burmeister (1988), Ammer (1993), Clare and Thomas (1994), Burmeister, Roll and Ross (1994), Azeez and Yonezawa (2006). When macroeconomic variables are to use, it is important to distinguish a priori the positive and negative effects on stock returns caused by a positive and negative shock of the macro-variable. Specifically, when positive shocks of a macroeconomic variable bring "good" news to investors, the derived risk premium relative to this factor should be positive. In contrast, when positive shocks of a variable bring "bad" news to investors, a negative risk premium should be found. These issues have been discussed by Burmeister and McElroy (1987) and Ammer (1993). Consider a factor of which, positive shocks cause stock prices to

[6] Many authors have pointed out this observation. For instance, see Chen (1983), Burmeister and Wall (1986), Hardouvelis (1988), Chen and Jordan (1993).

increase in general. Betas associated with this risk have a positive sign and a positive premium per unit of exposure indicates that investors require more compensations on stocks of which prices have higher positive correlation with innovations of this factor. In a counterexample, if positive shocks associated with a systematic factor cause stock prices to fall in general, then the betas will have a negative sign. A negative premium relevant to this factor means that investors find appealing to invest in those stocks of which prices increase with positive shocks of the factor. Investors will thus require more compensations to those stocks of which prices fall to positive news. To understand this, the product of negative betas multiplied by the negative risk premium returns to a positive amount in the basic equation of APT, indicating that investors require compensations as it contributes positively to expected returns. A positive beta multiplied by a negative risk premium per unit of beta equals a negative amount, that is a negative contribution to expected returns.

4.4.2 Candidate Macroeconomic Variables

One of the weaknesses of the APT, is the lack of a theoretical guidance about the identification of the risk factors. Consequently, all the efforts in choosing *innovations* that may affect stock returns is somewhat arbitrary but should be consistent to what theory expects it affects stock prices. Since we do not have a priori knowledge about their identity, sign, or value, Chen et al. (1986) used the present value model of stock prices as a driver to choose candidate variables, that is,

$$P_{i0} = \sum_{t=1}^{\infty} \frac{E[D_{it}]}{(1+r)^t} \tag{4.1}$$

where, $E[D_{it}]$ is the expected value of any dividend paid at period between t-1 and t, and r is the discount rate. They argue that systematic forces should affect at least one of the above parameters of the model and add that expected cash flows are influenced by both nominal and real changes. It is reasonable to think that inflation would have an impact on those future cash flows and the discount rate. Moreover, changes in the real production would affect future cash flows in real terms. Interest rates should also have an impact on stock prices as the discount rate is an average of rates over time. Hence, the level of interest rates and the term structure (time value of money) cause changes to the discount factor, i.e. denominator of (4.1). Since the discount rate also contains a risk premium, unanticipated changes of the latter one, would affect stock prices. To make this work more comprehensive, we will present the main variables have already tested in previous studies and/or are variables we used in this study. Apparently, many other variables have been tested in the past, such the Money Supply (M2) in UK. Selection of the series should depend (we believe) on the state of economy tested (i.e. Open economy, emerging etc.) and most notably on the economic interpretation of the series. Presuming the dollar’s value as a priced factor in the US for instance is less likely to hold true, but in an emerging country, exchange rates could play a leading role on asset prices.

Inflation

Inflation, as a condition of rising prices in the economy affects both the expected future cash flows and the discount rate. For instance, when the prices of raw materials rise, the companies' expenses increase and subsequently earnings mitigate. The lower earnings per share are often linked with lower dividends per share. Another effect of inflation is relative to the revenues of goods sold. When prices in the economy raise, the basket of consumer goods and services becomes more expensive and hence, an average consumer affords to buy less quantities. This argument results in the same effect as the companies' revenues decrease. When inflation exceeds the target set by the monetary policy, Federal Reserve will try to mitigate inflation by raising interest rates. Interest rates are positively related to inflation. There are thus many scenarios about the stock price movements, in contrast to the bond prices which are negatively related to interest rate movements. Assuming a positive scenario where the firms are able to increase their prices, they may experience an increase in growth which will also increase the growth rate of dividends and this may offset the higher required rate of return due to increases in interest rates. If the offset is overall, theoretically would not cause a stock price movement. Another plausible scenario is when firms cannot increase their prices of goods sold but costs increase. The growth rate of returns will then decline, and so will do the growth rate of dividends. Consequently, stock prices will fall as interest rates will cause a positive effect on the required rate of return and expected future cash flows will be reduced. Assuming investors are rational and well informed, they will adjust the expected inflation rate on their estimations of expected future cash flows. In other words, when they anticipate an inflation rate increment, they will raise their required rates to protect from a fall in real rates. Unanticipated inflation though, which is the portion of inflation rate that investors did not expect, will make ex-post real rates differ from the corresponding ex-ante rates. Therefore, we expect investors are compensated for this uncertainty systematically.

So far, two variables have been used in the relevant literature to capture the effects of inflation. The first one measures directly the unanticipated inflation as:

$$UI(t) = I(t) - E[I(t)|\ t-1] \tag{4.2}$$

where,

$$I(t)= \ln(CPI(t)/CPI(t-1)) \tag{4.3}$$

The first variable in the RHS of (4.2) is the monthly inflation rate as measured by the natural logarithmic differences of Consumer Price Index (as presented in (4.3)). The second variable denotes the expected inflation rate at the end of month t based on all the available information at the end of previous month. Chen et al. (1986) and Chan et al. (1985) obtained series of expected inflation from Fama and Gibbons (1984), who derive it from Fisher equation. The second variable is, changes in expected inflation:

$$DEI(t)= E[I(t+1)|t] - E[I(t)|\ t-1] \tag{4.4}$$

Chen et al. (1986) assume this series follows a martingale. If this is the case, then the expected value on next month will be the present (realized) value and hence the variable could be treated as an innovation. They reason that if investors re-estimate ex-ante inflation due to economic factors and not only by forecasting errors, this variable would contain an extra information that is not involved in (4.2). Hamao (1988) in Japan, used the repurchase agreement rate in the *Gensaki* market as a proxy for the short-term risk-free rate when applying the methodology of Fama and Gibbons (1984) to derive the Expected component of Inflation and in sequence the two series related to inflation (4.2) and (4.4). We do not consider (4.4) in our sample however for two reasons. The first one is the poor power it seems to have considering the empirical results of previous works. The second and most notably is because we include the EPU index which has been constructed by Baker, Bloom and Davis (2013, 2016) and includes a sub-index measuring disagreements about inflation among investors. Thus, we expect by taking the first differences of this index to capture, even in a mediate way, changes in expectations about inflation. Unfortunately, this sub-index changes quarterly, in contrast with the series of equation (4.4) which changes in a monthly basis, but we believe it gives more reliable results since it measures how the forecasts among investors differ. Equation (4.4) remain a good proxy, econometrically only, when there is no better way to obtain real-world data and also requires the assumption of being a martingale which is not necessarily true. More about the EPU index is described below.

Industrial Production

The expected future cash flows in equation (4.1) depend on the level of real aggregate activity, as the required rates do. There is a strong relationship between securities markets and the economy, where the former reflects expectations about the latter. Fama (1981) finds returns on stocks to be correlated with the future growth of output. Siegel (1991) in a study using US data finds investors could earn greater returns just by switching from stock markets to the riskless short-term bonds and vice versa, if they predict the future state or if they know the current state of the US economy (i.e. whether the economy experiences a recession or expansion). A recent study by Conover et al. (2016) reveals that investors can also still earn excess returns if they turn from stock markets to bonds (and vice versa) one month after the trough (peak).

Gross Domestic Product is a basic indicator of the current state of the economy, but it releases in a quarter or annual basis. Maybe a more comprehensive way to examine the growth of production, even more frequently in a monthly basis, is by using the Industrial Production Index. Industrial Production index measures the real output of industries including manufacturing, mining, electric and gas[7]. The Conference Board classifies IP index among the *coincident* business cycle indexes, meaning that when changes in the aggregate activity occur, IP index captures these changes almost contemporaneously. A large variation in economic growth is due to fluctuations occurred in industrial sector. Chen et al (1986) use the natural logarithmic difference of the index of Industrial Production between month t and t-1 and lead it by one month in order to make it contemporaneous with the other variables. To understand this, since investors use all the available information, current prices should adjust for future changes in industrial production. Leading the series by *only*

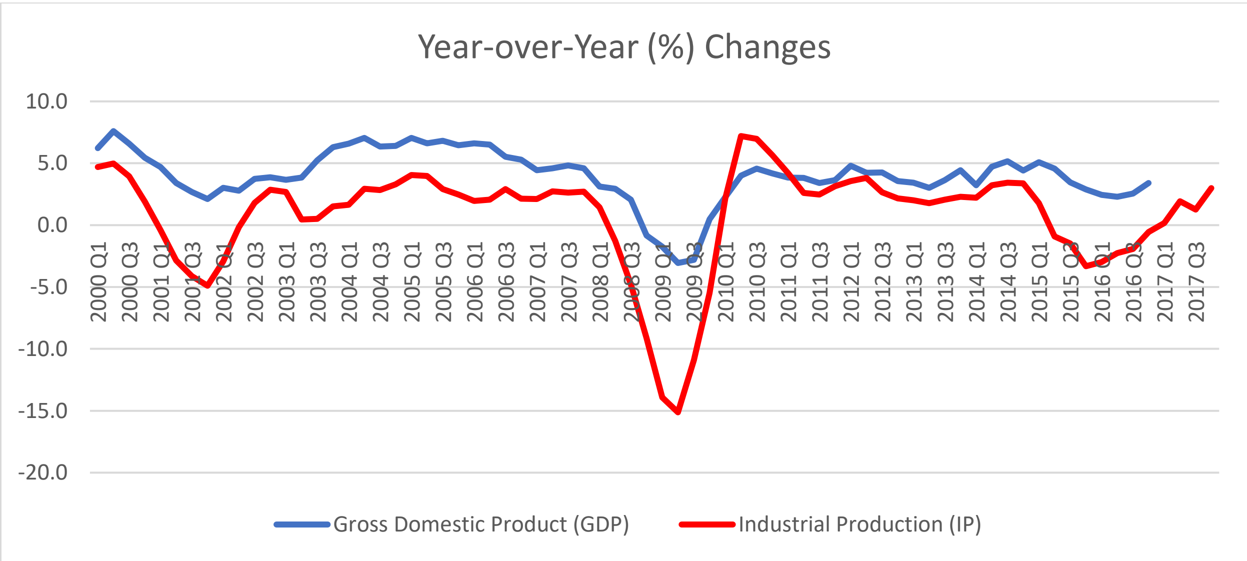
[7] The Board of Governors of the Federal Reserve System provides a detailed description of IP index.

one month, seems rather an informal agreement than a compulsory. In their study they find unanticipated changes in the growth rate of industrial production to be a priced factor. Again, the same proxy has been used in other papers i.e. from Chan et al (1985) and Hamao (1988) who also had adjusted the series for seasonality, an issue which was observed by Chen et al (1986) but not corrected. Clare and Thomas (1994) used lags of the realization of the index to adjust the series to the month when the index is announced to investors, claiming they want to measure how investors react to shocks of the announcement. They also used unadjusted data for seasonality to reflect the exact value the investors observe.

When the aggregate activity plunges, industries tend to postpone their outputs since sales are expected to drop in the near future and inventory costs increase. Production recovery will occur when expectations are being improved. Companies will then be compelled to increase their outputs in an attempt to respond to competition. Otherwise, they will be inadequate to face the increasing demand and competitive companies will drop them out of competition. Opportunity costs in this worst-case scenario will have damaging effects. Since investors are assumed to anticipate future impacts of all these events, they will react by selling stocks when aggregate activities are expected to go down and will pressure the marketable securities to meet their fair prices when business cycle is unfavorable. Figure 4.1 depicts the year over year percent changes of Gross Domestic Product and Industrial Production index for every quarter between the period 2000 and 2017.

Figure 4.1

The following line-graph compares the movements of Gross Domestic Product (GDP) with Industrial Production index (IP) in the US from 2000 through 2017. Blue (Red) line reveals the YoY percent changes of GDP (IP). Series of GDP and IP were found from the Federal Reserve Bank of St. Louis.



Term Structure

«***Interest rates are also important because they represent opportunity costs***» (Chan, Chen, & Hsieh, 1985). Reilly and Brown (2003) regard interest rates as exchange rates between current and future consumption. The discount rate can be decomposed into two parts, the risk-free rate and a risk premium. Ignoring any other type of risk, future cash flows are sensitive to changes in interest rates due to the *time value of money*. Since the discount rate is an average of rates over time, any changes in the risk-free rate would cause the discounted cash flows change in value. There is a debate in the literature about which rate is considered as an appropriate free of risk, but it is commonly accepted to use Federal Funds rate or any of the Treasury Bill or Government Bond issued from the US Government as a proxy since they are almost free of default risk.

In addition, according to the *Expectations hypothesis,* long-term interest rates indicate the expected level of future short-term interest rates, and a rise in the long-term relative to the short-term rates is due to the market expectations about future short-term rates. Consistent with this hypothesis for the US rates are findings from Hardouvelis (1988) and Fama (1990) among others[8]. The yield curve which connects all those rates provides superior information about the future activity of an economy. In its simplest form, regarding only the yields of, say, the 10-year Government Bond and the 3-month Treasury Bill, the spread of those two yields measures the *slope of the yield curve*. An upward sloping yield curve implies a faster future growth rate of real output. To understand this, normally the yield of long-term government bonds exceeds the corresponding yield of short-term bonds, as investors are compensated with a liquidity premium. When the long-term yields are rising faster than the short-term ones, prices of the former decline more than the prices of short-term bonds, which attracts investors to place their money on the long-term assets. As future short-term bond rates are expected to rise, agents anticipate increases on inflation rates and the economic activity. Banks' willingness to provide loans increases as well. When slope becomes flatter though, which means the spread narrows, this is an evidence of slower expected growth rate of real output. Investors expect stable inflation and interest rates and there is a poor willingness to approve long-term loans from the perspective of banks. Since the intercept is positive, a negative slope does not necessarily indicate a slowdown in economic activity, but a slow pace of growth could be the case. It seems natural to regard changes in the term structure as a risk affected by the monetary policy, but Estrella and Hardouvelis (1991) provide evidence that the yield curve captures, inter alia, factors that are not controlled by the monetary policy.

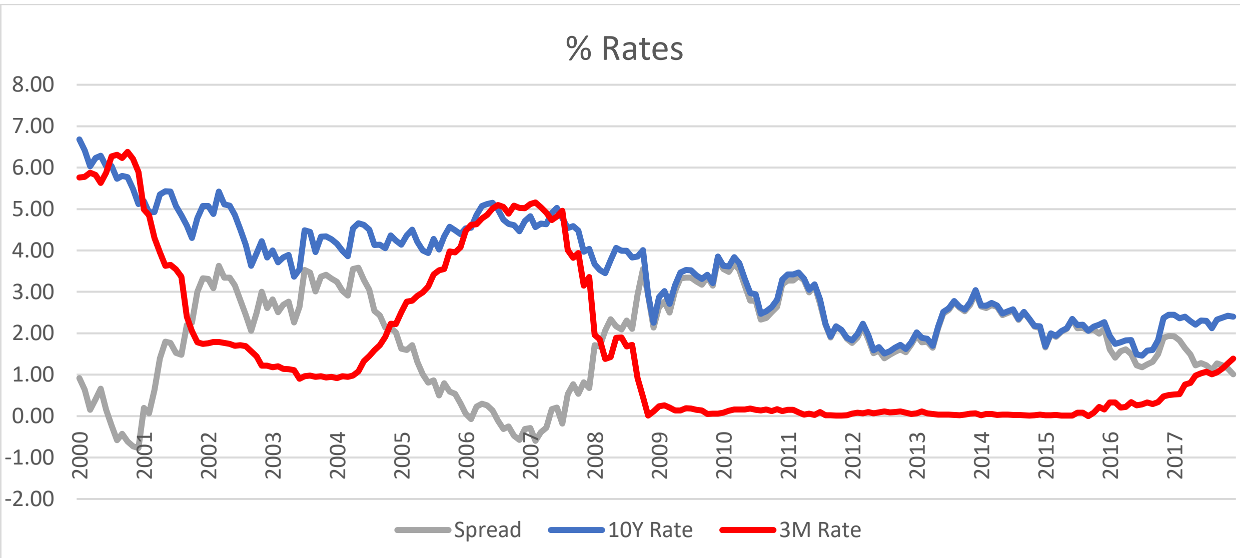
In their multifactor models to test APT, Chen et al. (1986) and Chan et al. (1985) used the returns series of a Portfolio of Long-term Government Bonds and the Treasury Bill rate known at previous month and applying to current month to measure changes in the term structure. They argue that under a risk-neutral world this series measures the unanticipated returns on long-term bonds. Hamao (1988) used the returns on long-term government bonds minus the Gensaki rate, arguing that yields in Japan are not the same as yield to maturity. All these studies regard changes in the term structure as a source of risk. Other studies however such those of Clare and Thomas (1994)

[8] Contrary to these findings Campbell and Shiller (1991) among others find that the interest rate spreads predict the wrong direction of future short rates.

use the term structure (Yield on long government bonds minus Yield on short government bonds) in levels. In our study we use the 10Y yield minus the 3M yield as a measure of the yield spread and use the first differences for two reasons. At first, we perceive this risk arises when the slope of the yield curve changes, and thus we want to test how stock prices react when the spread changes, and secondly, we found the series non-stationary in levels.

Figure 4.2

This line graph depicts the spread between the 10Y and 3M Treasury yields in the US for the period from 2000 through 2017. Blue line shows the yield of 10Y US Treasury (constant maturity). Red line represents the yield of the 3M US Treasury (constant maturity). Grey line is the spread. Series for these yields were found from the Federal Reserve Bank of St. Louis.



Default Premium

Despite the time value of money, investors are compensated for investing their money in risky assets. The riskier an asset is, the higher its expected returns should be. Otherwise, the demand for such an asset would be zero in a world of rational and risk-averse investors. The discount rate contains a premium for such a risk. In an attempt to measure the unanticipated movement of risk aversion, Chen et al. (1986), Burmeister and Wall (1986) and Chan et al. (1985) employ the following series:

$$UPR(t) = \text{“Baa and under”}(t) - LGB(t) \quad (4.5)$$

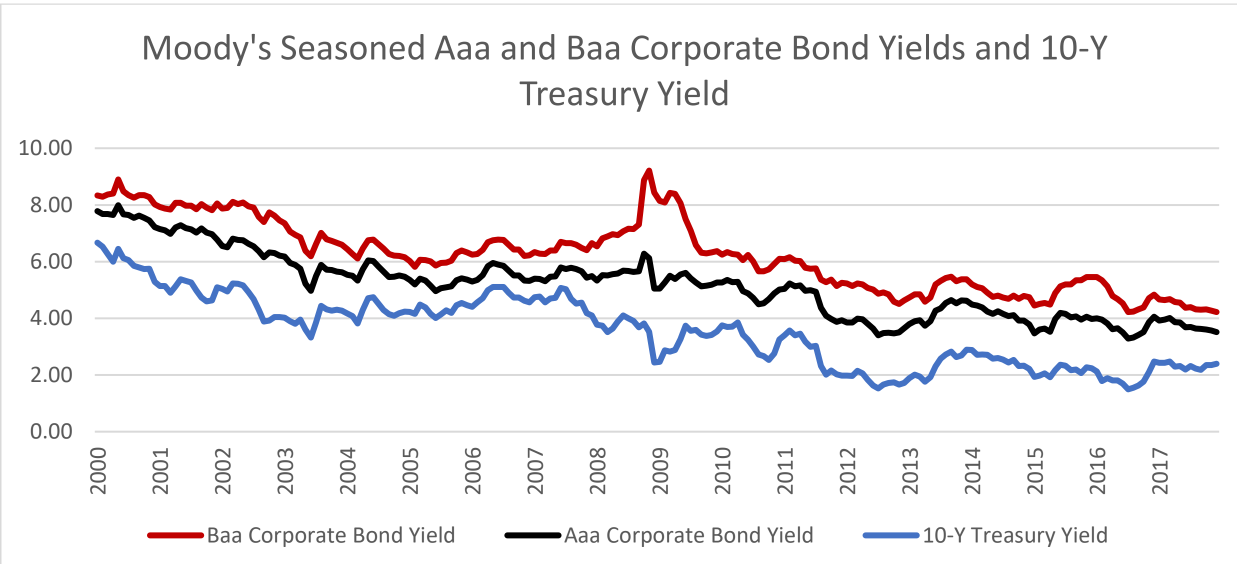
where, “Baa and under”(t) is the monthly return on a portfolio of corporate bonds with a “Baa and under” rating class and LGB(t) is the monthly return on a portfolio of long-term government bonds. Burmeister and Wall (1986) argue this factor ***“…captures a leverage effect in that highly levered***

firms should be more sensitive to changes in it" and that it ***"may measure the extent to which portfolio managers view equities and government bonds as substitutes"***. Hamao (1988) in Japan used the returns of long-term government bonds with 10 years of maturity to subtract from the returns on a portfolio of bonds issued by electricity companies with the same years of maturity. Another proxy for the same factor has also presented as an alternative in his study by subtracting (the same) long-term government bonds returns from a managed fund return. The problem with the managed fund is that, it contains both corporate and government bonds and has an average maturity of eight years. On the other side, electricity bonds returns should not serve for the high yield bond premia and contain fluctuations related to this specific industry. Hence, even if other series were not available for this variable, we should be skeptical when interpreting these premia. Clare and Thomas (1994) in the UK define the default risk as the difference between Debenture and Loan Red-Yield and the Yield on Long Government Bonds and use this difference at level, since, as they claim, Chen et al (1986) and Chan et al (1985) use this variable at level. We claim though, the difference between two yields doesn't account for how the risk aversion changes through time. Chen et al (1986) differenced the returns between two bond portfolios, and not the yields of an index, to mitigate the effect of time-value of money and to estimate the evolution of the premia. When returns of the junk bond portfolio are negative and higher in absolute value than the negative returns of the long-term government portfolio, this indicates the prices of the former lowered much higher due to the higher yield investors required through the certain period. Recall that bond prices are inversely related to the interest rates of an economy and change to adjust for the movements of the latter. Investors require higher yields in more uncertain times or investments. Therefore, yields are somehow connected with the business cycle. In the case of just differencing yields of two indices though, one is only estimating the risk premium in a certain period but tells nothing about how much this premium has changed. Assuming in an extreme case that the spread doesn't change through time, it would be sufficient to claim that agents discount this spread when forming their expectations about assets' performance. Clearly, the unanticipated movement of this spread contains information about how investors change their risk tolerance when markets experience more or less uncertainty. Chen and Jordan (1993) also use the difference between the yields of Aaa and Baa to capture changes in risk-premium. Based on our arguments discussed above, in our study we use the spread between Corporate Baa Bond Yield (ranked by Moody's) and the 10-year treasury yield with constant maturity at the end of month (t) and take the first difference of this spread, to account for monthly changes of the default yield spread from period *t-1* to *t*. Constant maturity helps us mitigate effects of inflation. Hence, the spread can be seen as the compensation of investors for default and liquidity risks and changes in the spread can be interpreted as changes in level of uncertainty.

In Figure 4.3 we compare the performance of three different bond indices according to their inherent risk of default for the period between 2000 and 2017. The first index (red line) measures the yields of Baa Corporate bonds as ranked by Moody's and the second index (black line) measures yields of Aaa ranked corporate bonds. The third line (blue) represents yields on Government bonds with 10 years of maturity. Apparently, Baa ranked securities offer higher yields due to higher probabilities of default as compared with Aaa ranked securities. Theoretically, investors who place their money on US Government bonds are not exposed to default risk, and thus yields of this category are even lower. High yield or "junk" bonds offer even higher yields compared to Baa's due to greater probabilities of the issuing-firms to get bankrupt. We can see that in times of the financial crisis of 2007-2008 the spread experienced a sharp widening and Baa's reached a peak in the early months of 2009. The spread shrinks almost at late of 2009.

Figure 4.3

This line graph compares two yields on corporate bonds with different rankings with the yields of the 10Y Treasury (constant maturity) in the US for the period from 2000 through 2017. Black (Red) line represents the yields of seasoned corporate bonds issued by firms with a rating of Aaa (Baa) grade according to Moody's credit rankings. Blue line figures the yields of the 10Y US Treasuries. Series of the three yields were available from the Federal Reserve Bank of St. Louis.



Economic Policy Uncertainty

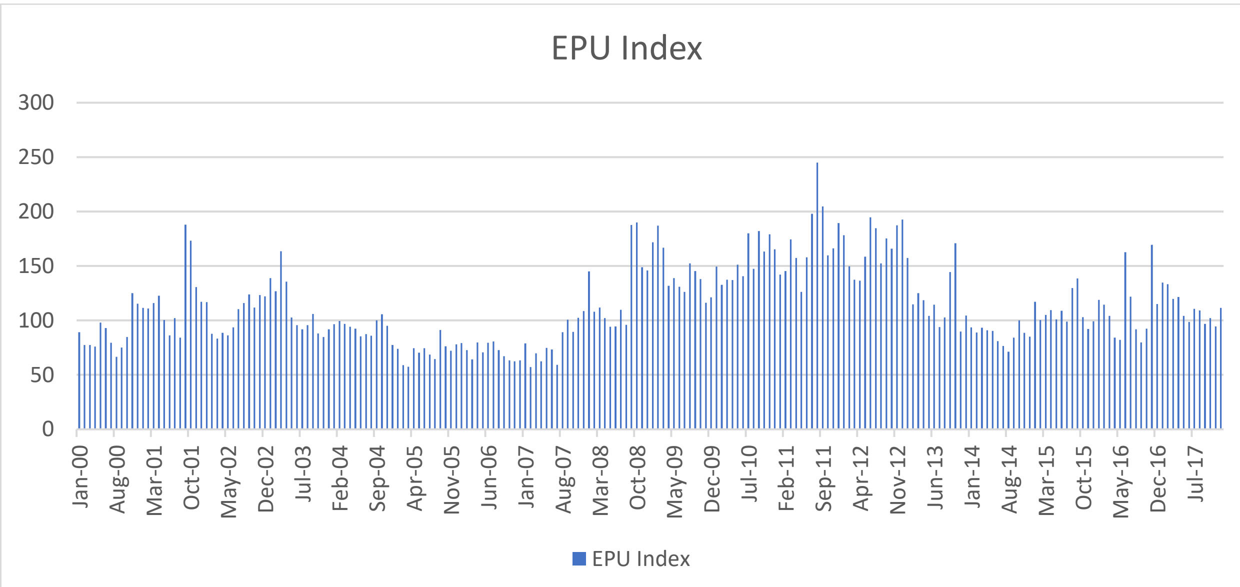
As we have presented above, APT requires factors to be associated with some characteristics, but it tells nothing about their identity. Previous studies have attempted to derive factors from macroeconomic variables or from the money markets. Ideally, we should regard these factors as exogenous in the pricing relationship of APT, but admittedly, all the macro-variables are in some extent endogenous due to their interaction in the system. Changes in the government policy for instance could be a source of risks and thus affect investors preferences, but the opposite is also plausible. Market could enforce Government policy to change. Nevertheless, changes in policy related to the Government (i.e. Fiscal, Tax, Monetary) brings uncertainty which matters for agents. When markets experience high levels of uncertainty, agents require higher returns on their investments and managers encounter raised costs of capital. This phenomenon might cause temporarily a lower productivity tempting until managers are able to have access to lower fund rates. Up to this point, changes in the risk premium described above (see default premium) should reflect all this uncertainty. So, why would we need another measure to capture uncertainty? We believe, a spread of risky bond yield in excess of the government bond yield would not explain alone all this variation of the uncertain environment. If there is an index responding to how uncertain an economy is due to policy affairs, and the components of this index are out-of-market determined and agents have access to, then changes of the value of such an index could followed by changes in agents' perception about the market's prospects.

Baker, Bloom and Davis (2013) have developed an index measuring policy-related economic uncertainty which consists of three components (sub-indices). The first sub-index (with the largest weights) measures policy-related economic uncertainty from the perspective of newspaper coverage. It searches for certain words and measures the intensity of large newspapers in the US to concerns about the economy, policy and uncertainty. The second sub-index measures instability and uncertainty about future taxes. It counts for the federal tax code provisions set to expire and their effects on tax revenues. Finally, the last component measures the extent of disagreements on forecasts about inflation and government purchases. These forecasts are provided, each quarter, by participants on the Survey of Professional Forecasters from the Federal Reserve Bank of Philadelphia. As mentioned above, Chen et al. (1986), measure changes in forecasts about inflation each month by extracting series of expected inflation from the Fishers Equation as proposed by Fama and Gibbons (1984). Although they derive this series by theory, in practice there are disagreements on expectations about inflation which is not captured by their model. This sub-index provides information about the extent of disagreements, despite the fact that surveys are published quarterly and not monthly. It also seems comprehensive since government purchases forecasts provide useful information about future outcomes and dispersion within forecasts indicates uncertainty. To construct their overall index, Baker, Bloom and Davis (2013) normalize each component by its own standard deviation and use weights of ½ for their first sub-index and 1/6 for each of the 3 remaining components (tax expirations, disagreements on inflation forecasts and disagreements on government purchases forecasts). The higher the value of the overall index the more the uncertainty is observed.

Baker et al. (2013) found large equity market jumps to have triggered by policy-related developments for the years 2008 to 2011. They also examined the sources of uncertainty in their EPU index and found that fiscal policy (i.e. tax and spending) and healthcare and entitlement policies were the main drivers of EPU index. To the contrary, they found no evidence of greater uncertainty related to monetary policy since 2008 in their news-based index. Furthermore, they found positive shocks in EPU index to forecast declines in investment, total output and employment. Brogaard and Detzel (2014) found that the EPU index proposed by Baker et al. (2013) forecasts stock market returns. They argue that government economic policy introduces non-diversifiable effects in the markets and that agents' decisions are affected by their expectations about policies adopted in the future. A critical question however is, from which channel does EPU affects stock returns in formula (4.1)? Brogaard and Detzel (2014) provide evidence that EPU does not affect dividend growth but it is the higher rates that pressure the stock prices to fall given the level of expected dividends stable. This finding has been corroborated by Phan, Sharma and Tran (2018) who test whether country-specific and global EPU predicts stock excess returns in 16 countries. In our study we use innovations of Baker et al.'s (2013) EPU index as a proxy for policy-related shocks to test whether uncertainty regarding fiscal, regulatory and monetary policy is a factor for which premia counts over and above the other observed factors. Since the largest component of the index is news-based, we can assume without a loss of generality that movements in this index reflect the agents' changing perceptions about uncertainty.

Figure 4.4

The following graph shows the policy uncertainty in the US for the period from 2000 through 2017. Economic Policy Uncertainty (EPU) index has been constructed by Baker, Bloom and Davis (2013) and its series is available from *http://www.policyuncertainty.com*. Index is normalized to have an average value of 100 from January 1985 through December 2009. An increment (reduction) denotes higher (lower) policy-related economic uncertainty in the US.



Developments in Technology Sector

As long as technology grows, productivity within the firms changes over time. Managers often come up with the dilemma to renew their equipment and change the production structure to become more competitive, though these plans are in most cases expensive. From one aspect, this implementation will render operational costs decrease and in sequence net income to rise. From another aspect, it may require a great funding and depending on the riskiness of the project, investors may require higher rates. In many cases, where managers are not willing to obtain a state-of-the-art equipment, competition could drop the firm out. Even if such an argument seems to affect firms in a micro level, consider the case where industries are well equipped, but a sudden technology innovation renders them obsolete, or when such an innovation drives a majority of investors to specific industries as they see future income. There is a relation between developments in high-technology sector and changes in consumption and investment opportunities. According to the National Bureau of Economic Research, one of the most relevant indicators of long-term economic prospects is productivity, and permanent increases in the latter are due to changes in technology. Basu, Fernald and Shapiro (2001) provide evidence that the productivity growth during the second half of the 1990s owes to an increase in technological growth.

We are concerned whether changes in the tech-sector activity account as a different source of risk in the US stock markets since it is a vital part of the US aggregate economy. Thus, in this study we try to answer if shocks occur in tech-sector have an explanatory power to stock price fluctuations. Hsu and Huang (2010) argue technology prospects should be positively related with aggregate consumption and investment opportunities in an intertemporal economy. They support that in promising technology prospects, investors tend to increase their consumption rates as they see higher income in the future. Firms will also adjust their investment plans and future dividend payouts depending on their production functions. According to findings from Cochrane (1996) expectations on investment returns are related to expected stock returns. Thus, a technology factor could be priced systematically by the markets.

Hsu and Huang (2010) have constructed a mimicking portfolio which captures technology factor based on the U.S. patent data, where positive (negative) innovations indicate better (worsen) aggregate technology prospects and implement several tests in three different models, the Merton's (1973) ICAPM, Fama and French's (1993) three factor model and Carhart's (1997) four-factor model and found positive premia associate with technology risk. Among their findings, technology factor could explain the momentum phenomenon and is a distinct priced factor. They also find that small growth stocks have a negative beta to this risk and attribute these findings to the fact that these firms raise investments on brighter technology prospects and pay less dividends to fund these investments, which imposes lower expected returns. Furthermore, low-tech stocks are quite more sensitive to fluctuations on technology factor and thus promise higher expected returns.

Hobijn, Stiroh and Antoniades (2003) composed the Tech Pulse Index consisting of coincident indicators of activity for the sector of information technology in the US. These indicators are "***investment in IT goods, consumption of personal computers and software, employment in the IT sector and industrial production of (and shipments by) the technology sector***"[9]. As movements of these indicators contain "noise", the index captures only their common trend. Tech Pulse Index can be thought as a summary statistic of the health of IT sector and according to findings from Hobijn et al. (2003) it can serve as a leading indicator of aggregate economic activity[10]. Another reason to consider an index measuring the state of technology is because shifts on this index may explain the well-known Technology Bubble of March 2000 in the US. The bubble burst lasted almost two years and affected many companies such communication, internet-based and online shopping. Many of these companies shut down, and from those which survived stock prices and market capitalization dropped dramatically in most cases.

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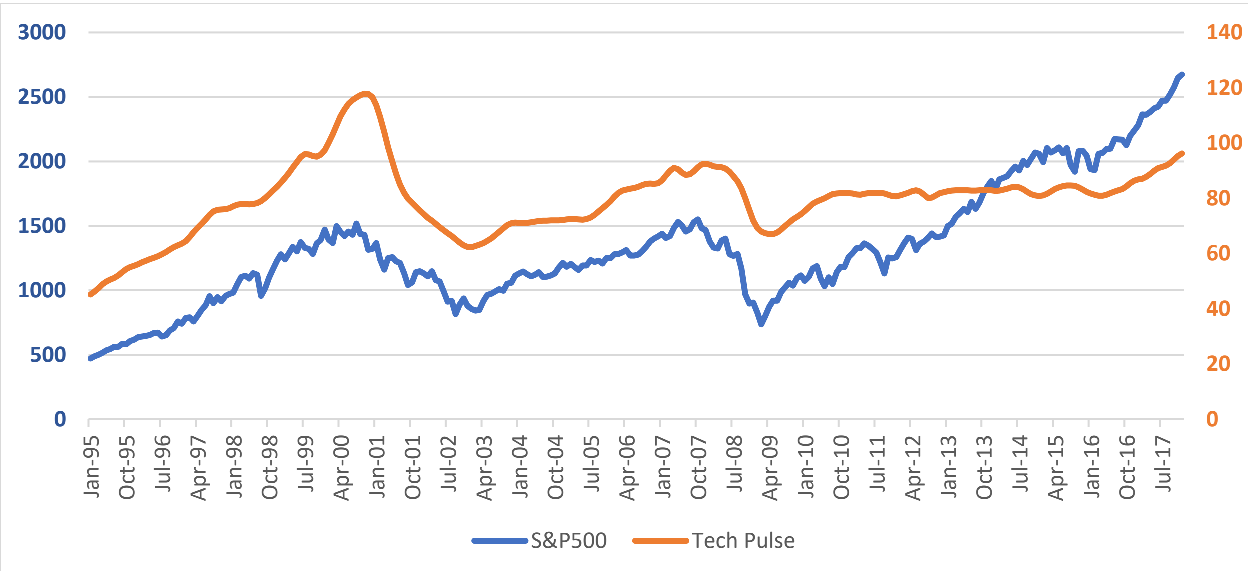
[9] Source: The official website of the Federal Reserve of San Francisco [https://www.frbsf.org].

[10] Specifically, Hobijn et al. (2003) notice the Tech-Pulse Index growth stagnated during the recessions of early 1980s, early 1990s and 2001. During the downturns of 1990s and 2001 the index could forecast GDP and its predictive power surpassed other indicators, though they did not analyze the causation but only correlations with aggregate activity.

Figure 4.5

This figure reveals the trends on *Tech Pulse Index* and *S&P500* for the period from 1995 through 2017. Blue line is related to S&P500 index (of which values are shown on the vertical axis on the left). Series of S&P500 were found from the Bloomberg Terminal. The line with orange color represents the San Francisco Tech Pulse index (of which values are shown on the vertical axis on the right-hand-side). Series of Tech Pulse index are available from the Federal Reserve Bank of St. Louis.



4.4.3 Derivation of Unanticipated Components

An important condition is that the 'news', or more formally the factor realizations, affecting ex post returns in the return generating process (3.23) given that investors have already formed their expectations, are strictly unexpected. This is equal to saying, the unanticipated components of each macro-variable or more generally the systematic factor should be a mean-zero serially uncorrelated white-noise process. Otherwise, these events would have been reflected by the agents when forming their expectations. Two techniques have been used widely in the literature so far to isolate the unanticipated components of the series. The first one is called the "*rate of change*" approach and is simply the use of the first differences of a series assuming it follows a random walk[11]. The method of the first differences has been used extensively in the literature[12] but it has been criticized since it has been observed that the first-differenced values are often autocorrelated, indicating that the condition of being a white-noise process doesn't hold[13]. The second is the use of an autoregressive AR(p) model, where (p) lagged values of the dependent variable are used to predict

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[11] If a series is a random walk process, then the expected value at the next time period equals the current value of the series. Hence, the difference of the ex-post values between two adjacent observations is assumed to be an unanticipated movement.

[12] i.e. Chen et al (1986), Chan et al (1985), Hamao (1988), Azeez and Yonezawa (2006), among others, use the rate of change approach. Clare and Thomas (1994) use the autoregressive approach.

[13] i.e. see Priestley (1996).

its current value and the residuals are the unpredictable components[14]. The second approach assumes implicitly that investors use autoregressive models on their predictions.

Priestley (1996) argues, even autoregressive models satisfy the requirement that the residuals are innovations, they require stable estimated parameters. He shows empirically that this is not the case for variables such the money supply, default risk, exchange rate, real industrial production, commodity prices and retail sales. Since coefficients are not invariant, if investors are assumed to use all the available past information, the use of autoregressive models would cause systematic forecast errors. Instead of the above techniques, Priestley (1996) suggests the Kalman filter approach which allows the agents to use a learning process when forming their expectations. In fact, Burmeister and Wall (1986) also used this technique to distinguish the unexpected movements of two observed factors (namely, Unexpected inflation and Unexpected growth in real final sales). The advantages of this approach are that there are not systematic forecasting errors by the agents, the procedure they follow is compatible with what to expect from theory and that the unanticipated components are innovations. When tested these three approaches in the content of the APT with prespecified macroeconomic factors, he confirmed the APT model with Kalman filter unanticipated components performs best both in-sample and out-of-sample.

4.4.4 Portfolios formation

Most studies use a Fama and MacBeth (1973) variant technique to derive priced factors. We will discuss this methodology later. This technique though induces an ***errors-in-variables problem*** when stock returns are regressed with the factors. This problem arises as the sensitivities, which are treated as independent variables in the basic equation of APT are estimates, having derived from a time-series regression on the factors, and are not the true values of the relative risk measure. To deal with this problem, the literature suggests forming and thus regressing portfolio returns instead of individual securities returns. If the errors in the securities betas are not perfectly positively correlated then portfolio betas are much more reliable estimates of the true (unknown) parameters than do individual betas (Fama & MacBeth, Risk, Return, and Equilibrium: Empirical Tests, 1973). Chen et al. (1986) grouped securities into portfolios based on their ‘size’ (as measured by the market value of equity) arguing they wanted to spread expected returns over a wide range and thus to enhance the cross-section power. Specifically, for each test period (calendar year), they arranged the sample securities in ascending order based on their Market Value of equity as reported at the end of previous year. They do not provide, however, any evidence whether this spread has accomplished or if it surpasses (in terms of returns spreading) other methods of constructing portfolios. The portfolios thus were re-arranged per annum and do not necessarily maintain their ‘size’ characteristics throughout the year. The same procedure was also followed by Chan et al (1985) and many other researchers testing the validity of APT with observed variables. Hamao (1988), let the portfolios re-arrange their securities per month, allowing them to be more

[14] Obviously, a special case of an autoregressive process is the random walk. In any case, the residuals of an AR(p) should be mean-zero serially uncorrelated, to regard them as unanticipated components.

synchronized. Clare and Thomas (1994) concerned the robustness of the macroeconomic factor model suggesting another alternative method of forming portfolios, based on securities' simple CAPM betas, but again, they let the portfolios re-arrange their securities per annum. A problem of Clare and Thomas' (1994) portfolios based on 'risk' is the ***regression phenomenon***. Fama and MacBeth (1973) suggest, the arrangement of securities based on the CAPM betas and thus the portfolio construction to occur in a period before the period of estimating portfolios' betas. However, Clare and Thomas (1994) point out that they were restricted to construct and estimate the portfolios' sensitivities within the same period as their entire sample period was not enough. Chen and Jordan (1993) and Azeez and Yonezawa (2006) grouped their sample securities in industry portfolios.

4.4.5 Methodology and Empirical Findings

Having derived the factors (as unanticipated components of macroeconomic variables) and having obtained the portfolio returns series most studies used a technique variant to Fama and MacBeth (1973) to estimate premiums. **Chen, Roll and Ross (1986)** tested stocks in the US for the period January 1953 to November 1983 and tests were made for the entire sample period and for three subperiods as well (January 1953 – December 1972, January 1973 – December 1977 and January 1978 – December 1983). The sample period was divided in these three subperiods **"…because it is often argued that the oil price jump in 1973 presaged a structural shift in the macro variables**" (Chen, Roll, & Ross, Economic Forces and the Stock Market, 1986). The variables they tested is the monthly first difference of industrial production index (MP), the yearly difference of industrial production index (YP), the monthly difference in expected inflation (DEI), unanticipated inflation (UI), changes in risk premia (UPR), and shifts in the yield curve (UTS). The derivation of those variables has already been described in subsection (4.4.2). The technique they used is the following:

1. At first, they select the sample of assets returns and construct 20 equal weighted portfolios.
2. The beta coefficients are being estimated by the time-series regressions of asset returns on the unanticipated changes of the state variables. Data of the first five years were used on this stage.
3. The estimated betas are then treated as independent variables in 12 cross-sectional regressions (one for each of the following 12 months) where the monthly returns are the dependent variables.
4. Steps (2) and (3) are repeated for each year in order to obtain time series of the risk-premium estimates for each macro-variable. The means of these time series are finally tested whether they statistically differ from zero with a t-test.

According to Chen et al. (1986) results, MP, UI and UPR were found to be significant over the entire period. UTS was also found to be marginally significant and DEI and UI were highly significant in a subperiod only. After removing YP which was not significant, the remaining state variables did not lose any of their power at all. Moreover, they tested the impact of two alternative market indices in NYSE (the equal weighted, EWNY, and value weighted index, VWNY) to compare their explanatory power with that of the state variables but found no significant pricing of these indices. Up to this point, an interpretation of the results is that market indices seem to not contain any missing priced factors and APT performs well against the CAPM. In addition, they tested the market indices in another fashion with the null hypothesis that market indices are efficient. These (asymmetric) tests could declared to be "less-fair" as they treat in favor of the market indices. Beta coefficients were not derived by a multivariate time-series regression but rather, beta coefficient of the market index (Value or Equally weighted) was derived by an "ordinary CAPM" test and the other state variables' beta coefficients were taken by the regression of the state variables alone (not including YP, or any of the market indices). On the regression with the Value-weighted index as a proxy for the market index, the results revealed the index remained significant over the entire period but had a negative sign, which comes in contrast to what to expect from theory, and the state variables did not lose their significance substantially with the addition of the index.

Following, they added a variable measuring the real per capita consumption growth as «***The intuition of the theory is that individuals will adjust their intertemporal consumption streams so as to hedge against changes in opportunity set***» (Chen, Roll, & Ross, Economic Forces and the Stock Market, 1986). Consumption-based theories argue that when the factors associated to the state variables are included in a model along with consumption, they will no longer have effect on pricing. The consumption betas however were found insignificant for both the overall period and the three subperiods and hence no relation between changes in consumption and pricing could extract. Even more, the estimated risk premium had a negative sign, which again comes in contrast to the theory, and the coefficients along with the significance of the state variables did not change effectively with the addition of CG. Similar to consumption changes, tests on the effect of oil prices changes (OG) occurred. Its beta was only found significant for the first subperiod (1958 – 1967). Moreover, the addition of OG series affected negatively the significance of industrial production (MP), but positively the risk-premium (UPR) and the term-structure (UTS) variables.

To sum up, Chen et al. made a serious attempt to define which economic variables explain the expected stock returns. They found that industrial production, changes in the risk premium and the term structure were highly related to the expected stock returns. They also found an effect of the unanticipated inflation and changes in expected inflation, but these variables were less powerful. **Chen et al. (1986)** state: «***We do not claim, of course, that we have exhaustively characterized the set of influential macro variables, but the set was chosen performed well against several other potential pricing sources***». Indeed, their test was pioneered as a first attempt to prove empirically that additional factors influence stock returns. These indications were in favor of the APT. Still important was their observation that stock market index had an insignificant influence on pricing when added with the state variables on the linear model, although its high relationship with the variability of stock returns.

Chan, Chen and Hsieh (1985) investigated the firm size effect using the multifactor model suggested by the 1983 working paper of Chen et al (1986) and found this model to capture a large portion of this anomaly. As for the monthly growth rate of Industrial Production, they adjusted the series for seasonality, a problem which had been observed but not corrected from Chen et al (1986). Chan et al (1985) analyzed firms listed on the NYSE during a 25-year period, from 1953 to 1977 and thus their sample was similar to the previous study. They followed the methodology of Chen et al (1986) but for their cross-sectional month-by-month regressions of the 20 portfolios on their betas they used a generalized least squares procedure to take into account the heteroskedasticity of the residuals, and again, having obtain the time-series of the coefficients (prices of risk) they estimated with a t-test whether they differ from zero.

What makes their work distinguished is their tests on the residuals in order to estimate if this model has explanatory power on the firm size effect. A first (univariate) test was implemented to see if the estimated residuals of the portfolio with the lowest market value stocks is different from the respective ones of the portfolio with the largest market value stocks. Theoretically, if the model is not able to capture this anomaly, small firms should possess larger estimated residuals than the large ones, since the residuals measure the difference of the realized (ex post) returns and the estimated expected returns. In addition, they tested the difference between top and bottom quintiles. A second test which was also implemented as additional diagnostics is a Hotelling T^2. Having the mean differences of the estimated residuals between each two adjacent portfolios, under the null hypothesis all these differences should be jointly equal to zero. Chan et al (1985) found positive prices for the Equal Weighted NYSE index (EWNY), the industrial production growth (IPISA) and changes in risk premia (UPR) as well as a positive intercept. In contrast unanticipated inflation (UTIB), changes in expected inflation (DEI) and unexpected changes of term structure (UTS) had a negative value. The intercept term was 0.00444 above the T-Bill 1Month of 0.00539 and the λ_1 was slightly lower than the realized averaged difference between the EWNY and the T-bill for the same period. For the overall period the significant prices of risk were those of IPISA, UITB and PREM, though the results varied in the two ten-year subperiods (1958-1967 and 1968-1977). For the first subperiod PREM and IPISA displayed statistically significant prices, in contrast to the second subperiod's PREM, UTIB and DEI. Analyzing the residuals of the 20 portfolios they found the smallest two portfolios to have positive average residuals and the largest three portfolios negative respectively. The Hotelling T^2 were insignificant and the magnitude of the residuals was generally small, though they exhibited some pattern. To assess the magnitude of each variable to the returns of every portfolio, Chan et al formed the products of the premia and the betas and found the EWNY component to be higher in absolute value than the other components. However, PREM explained the largest portion of the difference between the returns of the top and bottom portfolios. Another observation was that UTIB could explain only a minor portion of this difference, even though its price was statistically significant.

Maybe the most important part of their work is the multiple cross-sectional regressions they run with and without the additional explanatory proxy of the natural logarithm of the portfolios Market Value (lnMV) and estimated that lnMV along with other variables are taking into account the same risk as their premiums became insignificant due to multicollinearity problems. Furthermore, they set as explanatory variables the EWNY along with PREM where reasonable results for both the intercept (as compared with the averaged Treasury Bill) and the market premium (as compared with the averaged realized excess return of the EWNY over the Treasury Bill) and the coefficient of PREM was statistically significant at the 5% level. In another test, IPISA was added with

EWNY and PREM, and its coefficient was also significant. Impressively, both final two tests displayed insignificant paired statistics and Hotelling T^2 statistics meaning that the differences of residuals between the extreme portfolios and the extreme quintiles as well as compared jointly in pairs (U1-U2, U2-U3, …, U19-U20) did not differ from zero significantly. Finally, in an attempt to test the impact of January effect by examining the average residuals of their multifactor model, January related residuals did not show any pattern except for the smallest portfolio, but the January residual difference between the smallest and the largest portfolios was significant. An important observation was that PREM displays significant seasonality on Januaries, and hence they tested whether this variable accidentally explained the firm size effect, as this effect is immediately associated with the January effect[15]. To do so, they left out the time series sensitivities on Januaries and run again the cross-sectional regressions. They found that PREM did not lose any of its power at all, indicating that this variable does not explain only the January effect.

Chan, Chen and Hsieh (1985) conclude that the multifactor model imposed by Chen, Roll and Ross could capture the firm size effect, and especially, the risk premium is mainly responsible for the differences in averaged returns between small and large sized firms. Small firms are riskier than large firms because of their more intense fluctuation as a response to changes in economic conditions and hence they compensate for this additional risk.

Hamao (1988) performed an empirical investigation of the APT in the Japanese economy parallel to Chen el al (1986) to examine the international robustness of the theory. In his analysis, he used monthly returns data from the Tokyo Stock Exchange Section I for the period January 1975 to December 1984. A total number of 1,066 companies was considered but each month many of them (ranging from 53 to 188) were excluded due to missing observations. Employing a variant of Fama and MacBeth (1973) methodology for the 10 years period, Hamao runs the time series regressions to get the beta coefficients of the variables related to industrial production, changes in expected inflation, unexpected inflation, risk premium and term structure, and then runs monthly cross-sectional regressions over the same period to obtain series of prices of risk. Obviously, this method implicitly assumes that the sensitivities of portfolio returns to the macroeconomic factors remain stable over the entire period, which is not true, or at least further tests are required to corroborate this strong assumption. Hamao (1988), apparently, by implementing this variant, he wanted to exploit all the sample of data on the second pass regression. He finds a marginal significance of the term structure and a statistical significance on all the remaining variables. When he introduced the changes in terms of trade, all of the above coefficients increased their significance, though terms of trade did not display any significance on its own. In contrast to terms of trade and the term structure, all of the other prices had a positive sign.

In another variant, Hamao runs time series regressions over a five-year period and obtains the beta coefficients to run the cross-sectional regression on the first month after this five-year period and repeats this procedure month-by-month only to obtain a five-year time series estimates of each price of risk. We find this variant more attractive, even if he sacrificed half of his sample, as the betas now are renewed each month to reflect changes in the exposure profile of the portfolios. The

[15] A motivated reader who wants to see how the January seasonal is associated with the firm size effect is strongly encouraged to read the empirical evidence of Keim (1983).

results were of lower significance though. A proxy for the risk premium, which uses a manage funds' portfolio returns as a high yield bond was quite weak in both variants of the procedure and dropped out. Staying in the second variation, changes in the terms of trade influenced negatively the significance of unexpected inflation and the term structure and did not appeared to be significant on its own, so unanticipated changes in foreign exchange rates substituted this variable but the later one reduced the price of industrial production and did not appear significant on its own. Similar results were obtained when oil prices substituted the exchange rates. Hamao concludes the last two variables have already been taken into account by other variables.

A next step was to check the performance of market indices when added to the final model of macroeconomic factors he produced. Using a similar technique to the respective tests of Chen et al (1986), Hamao (1988) finds a superiority of APT against the CAPM. He finally argues to have found consistent signs for the prices of risk though the two inflation-related variables have the opposite signs of these found by Chen et al (1986). He interprets this result as being more valuable stocks those which bear a positive sign to inflation and the opposite holds for terms of trade which was found with a negative sign. Hamao's (1988) data had many flaws. Apparently, Japan could not offer the availability to important economic data through this period and thus, the candidate variables even as 'best' alternatives, should interpret with some caveats whether they could capture the inherent risks. Another problem we found, is the absence of the intercept values on his cross-sectional regressions. If the model is an appropriate APT model, then the intercept should reflect the risk-free rate, on average, through the test period.

More recently, **A.A. Azeez and Yasuhiro Yonezawa (2006)** performed another test of the APT with prespecified macroeconomic factors in Japan. Aiming to analyze whether macroeconomic factors could explain the well-known "bubble" in the stock prices at late 1980s, they used the methodology of iterated non-linear seemingly unrelated regressions to estimate risk premiums as introduced by McElroy and Burmeister (1988). Their sample consists of monthly data on all the securities trading on the TSE section I from 1973 through 1998 and they divide this time interval into three subperiods, the pre-bubble (1973-1979), the bubble (1980-1989) and the post-bubble period (1990-1998). Stocks were grouped into industry portfolios and the monthly portfolio returns were excess of a proxy for the risk-free rate, the overnight call money rate. The macroeconomic variables they tested is unanticipated shocks to money supply, inflation, industrial production, the term structure, the exchange rate and finally the growth rate of Commercial Land Price Index, since it was a common perception that the rising value of land increased the corporations' assets and the levels of stock prices in the bubble period. The later variable was interpolated linearly to monthly series as it releases twice a year. The method of interpolation though should be suspected a priori that may not reflect monthly shocks of this variable, and hence spurious relationship could reveal. More importantly, Azzez and Yonezawa (2006) claim to have used simple 'rate of change' to derive the factors and when attempted to generate innovations from VAR models, the results were not satisfactory enough. Since they do not provide any evidence about the serial correlations of the factors, it is reasonable to think the variables are violated in terms of predictability and hence could not serve as APT factors.

Bearing in mind these weaknesses, their findings suggest four variables to be priced systematically during each subperiod, the money supply, inflation, exchange rate and industrial production. Consistent with what should be expected, their magnitude increases in the bubble and post-bubble periods and their signs remain almost unchanged over time. Post-bubble period however shows higher variances of the premiums. They interpret these results as that investors are compensated for the “crash-risk” they undertake. The term structure of interest rates is priced depending on the subperiod. When all industries are examined the term structure was significant at 1% level only in the pre-bubble period whilst the same value was significant at 5% in the bubble period only when the manufacturing industries were examined. Land price seems not to be a priced factor in any of these cases but when Housing Rent Index substituted Commercial Land Price Index, Land price became significant. The supportive results for the exchange rate factor come in contrast to Hamao’s (1988) results who reported to have found exchange rates insignificant.

Su-Jane Chen and Bradford D. Jordan (1993) conducted a series of experiments to compare the ability of the Factor Loading Model (FLM) and a Macroeconomic Variable Model (MVM) to predict security returns. In contrast to many other researchers, they did not attempt to check for the validity of APT, but to compare those two different models in nature which have been used extensively in the literature as means to examine the APT. Their sample consists of 691 securities listed on the NY or ASE stock exchanges and 69 industry portfolios were constructed to calculate their monthly returns from January 1971 to December 1986. As for their first model, they obtained the factor loadings using maximum likelihood factor analysis and having assumed a number of 5 factors is sufficient. As for their second model, following the seminal work of Chen et al, they implemented a multifactor model with the following prespecified variables:

- Unexpected change in the term structure (UTS)
- Unexpected change in risk premiums (PR)
- Change in expected inflation (CEI)
- Unexpected inflation rate (UI)
- Unexpected change in the growth rate of industrial production (led by one month) (LGI)
- Percentage change in oil prices (led by one month) (LGO)
- The CRSP value-weighted index returns as the market index returns

In contrast to Chen et al (1986), Chen and Jordan (1993) treated the residuals of an AR(1) for each of the three variables PR, LGI and LGO, since they exhibited a serial correlation pattern. To test whether these macro-variables are correlated with the factors derived from FLM, they regressed the factor scores (which are estimations on risk premiums) on the seven macro-variables. Inflation-related variables were not significantly related to the factor scores and changes in industrial production could explain only marginally these scores. They concern that measurement errors on these index-based variables may shadow their significance. On the opposite, the remaining four variables were significantly related to the risk premiums. Changes in oil prices could explain a large portion of the first factor. This result was consistent with the high values of factor loadings of oil companies in the sample. In addition, they found the third factor to be significantly related to UTS and again, public utility stocks and commercial banks were found sensitive to this factor.

To make these two models comparable they applied a version of the two-pass regressions of Fama and MacBeth (1973), even if factor analysis can produce estimates of the factor loadings and the factor scores simultaneously. Another reason for doing so, was the re-estimation of the risk premia since excess portfolio returns would be used in the second pass. By doing so, they let the risk-free rate parameter to change per month. Otherwise, the model would estimate an average of the risk-free rate in the intercept. In the first pass, 69 OLS time-series regressions of the realized portfolio returns on the factors were applied and the resultant factor betas were used as independent variables in the second pass 192 cross-sectional GLS regressions with the dependent variables being the excess portfolios returns on each of the 192 months. They next compared both models (FLM and MVM) with three criteria. The first was the Davidson and MacKinnon (1981) test, the second the Theil's U^2 test and the third one a rather weak test of the APT which is simply the second-pass cross-sectional regression on the average excess portfolio returns this time. Hence, the weak test examines the result of a single cross-sectional regression.

Results of Chen and Jordan's (1993) analysis revealed a better performance of FLM to the MVM in predicting portfolio returns. At the 5% level, FLM outperformed MVM according to Davidson and Mackinnon and Theil's U^2 results. Based on the test suggested as the third criteria, both models' R^2 was over .30 but FLM was marginally preferred. In contrast to Chen et al (1986), they found that besides the market index, changes in expected inflation and changes in oil prices to be potential systematic factors. They reason this different finding could arise due to the different sample period, different portfolios formation or due to the autocorrelation observed in the Chen et al's (1986) series. They also found that the excess zero-beta portfolio return as measured by the alpha coefficient was not zero as theory suggested. It was found to be smaller in the case of MVM however, which gives an evidence of being a more appropriate model. To further estimate the appropriateness of these models, Chen and Jordan applied holdout sample tests by examining another 250 securities included in 30 equally weighted portfolios according to their sample mean returns and another out-of-sample test by dividing the entire period into two sub-periods: the base period (1971-1978) and the test period (1979-1986). Holdout sample results indicated a superiority of MVM over the FLM. According to the second criteria, in the two-thirds of the portfolios MVM outperformed FLM. Only the third criteria gave results in favor of the FLM. According to the ex-ante testing results of the second alternative test series, again the MVM's forecasting ability of the ex-ante portfolio excess returns was greater than the reported FLM's ability[16].

Mc Elroy, Burmeister and Wall (1985) showed that by substituting equation (3.32) into (3.25) the following equation:

$$R_i = \lambda_0(t) + \sum_{j=1}^{K} b_{ij}\,\lambda_j + \sum_{j=1}^{K} b_{ij}\,f_j(t) + e_i(t) \tag{4.6}$$

along with the assumption of N<T when the K factors are observed, is a system of N non-linear regression equations with N-K across-equation restrictions. Using non-linear seemingly unrelated

[16] With the Davidson and Mackinnon test it was found that both MVM and FLM's forecasting ability was not statistically different one another and the Theil's U^2 test suggested a superiority of MVM in 21 over the 30 portfolios.

regression techniques the parameters $b_{ij}$and λ_j can be jointly estimated and these estimators are consistent and asymptotically normal. In addition, they showed that if the errors are jointly normal, then the estimators are also maximum likelihood estimators. An advantage of applying non-linear seemingly unrelated regressions is that, one has not to construct portfolios of stocks to test the theory since this method eliminates the errors-in-variables problem (see Burmeister and McElroy (1988)). Their suggested methodology however is constraint to the extent that time-series observations should be greater than the securities tested in the model. Moreover, such models impose restrictions on covariances of residuals. Burmeister and McElroy contributed to the development and empirical assessment of the APT. In a series of published works, they introduce the residual market factor as an unobserved factor and construct an APT model containing both unobservable and observable factors. Burmeister and McElroy (1991) claim that if among the K factors, K-1 are observed and the Kth is unobserved, then, considering a large and well-diversified portfolio m exists (not necessarily the market portfolio), they derive the *fundamental pricing identity* which relates the excess returns on the m portfolio (λ_m) to the first K-1 observed factors' prices of risk ($\lambda_j's$) and to the price of risk of the (unobserved) residual market factor (λ_k):

$$\lambda_m = E[R_m(t)] - \lambda_0(t) = \sum_{j=1}^{K-1} b_{mj}\,\lambda_j + \lambda_K \tag{4.7}$$

where b_{mj} is the portfolio's m return sensitivity to the j-th factor. In sequence, they present a new equation which is testable with non-linear seemingly unrelated regression approach:

$$R_i(t) = \lambda_0(t) + \sum_{j=1}^{K-1} \beta_{ij}\,\lambda_j + b_{iK}\,\lambda_m + \sum_{j=1}^{K-1} \beta_{ij}\,f_j(t) + b_{iK}\,f_m(t) + \varepsilon_i(t) \tag{4.8}$$

where $f_m(t)$= $R_m(t)$ - $\lambda_0(t)$ - λ_m and β_{ij}=b_{ij} - $b_{iK}b_{mj}$ for i=1, 2,…,N and j=1, 2, …,K.

Burmeister and Wall (1986) were the first to introduce the *residual market factor* as the least squares' residual of a regression where the dependent value is the returns on portfolio m and the explanatory variables are the K-1 observed factors and McElroy and Burmeister (1985, 1988) and Burmeister and McElroy (1988) implemented this idea as a proxy for the unobserved factor. In our study, we attempted to include the residual market risk by regressing S&P500 returns with the observed factors to capture any other unobserved risk factor which systematically affects returns on this index. S&P500 can be thought as a well-diversified portfolio of stocks and therefore, anytime the index is expected to fluctuate due to pervasive forces only. Unfortunately, the inclusion of this unobserved factor deteriorated the pricing results of the model, and premia were not consistent with theory, so we excluded residual market risk from our model.

Beenstock and Chan (1988) tested the APT with macroeconomic variables with a sample of 760 UK security returns over the period October 1977 to December 1983, using a quite different approach with two different methods of iteration and found four factors affecting the UK stock returns. These were, interest rates, fuel and material costs, money supply and inflation, but the results were in general sensitive to the method of iteration.

Clare and Thomas (1994) analyzed stock returns in the UK stock market for the period between 1983 and 1990 for 840 randomly chosen stocks. They used two different techniques to construct portfolios, one based on the securities' 'size' and another based on securities' exposure to the market risk, to check for the robustness of Chen et al.'s (1986) procedure. In their work, applying the technique of Chen et al (1986) which is based on the Fama-MacBeth (1973) variant technique, they test for priced risks of 18 macroeconomic variables including Default Risk, Term Structure, Real retail sales, Current account balance, Exchange rate, Unemployment and Gold price among others. Starting with a test of all 18 macroeconomic variables, they drop out the most insignificant variable to finally conclude to a simplified model with only significant variables included in. They claim to use unadjusted series of the macro-variables and to lag/lead series when necessary to reflect the available information to agents as announcement times in some cases differ from event times (i.e. inflation rate announced in current month may have occurred in the previous month). There are however some issues to concern for their seasonally unadjusted series. It is well known that seasonally adjustments remove only the predictable ups and downs. Any irregular component and the trend, however, remain in the series. Since we are interested in the random noises of the series, seasonal adjusted data do not prevent the analysis. In contrary, it eases any analysis related to short-term or long-term development of the series. Do derive the factors they used the residuals from autoregressive models and have examined for the presence of systematic errors. This method makes the results to be, at least, more reliable than other studies which simply regarded first differences.

Using the 'beta sorted' portfolios, they find six significant prices of risk (Oil price, Debenture and Loan Redemption yield, Default risk, Consol. Yield/Dy, Retail price index, Private sector bank lending and Current Account Balance). The only variable with a negative risk premium is the Oil price. In contrast to Chen et al. (1986) they find a positive price for inflation. They also find a positive and statistically significant constant which indicates omitted variables in their model, since they use excess portfolio returns as the dependent variable. By adding the excess market return on their model, they find neither a significant price nor the price of the other variables affected remarkably. Turning to their second technique of 'market-value sorted' portfolios, they found quite different results[17]. They found the appropriate reduced model was that of only two variables included (Consol. Yield/Dy and Retail Price Index) with positive and statistically significant prices of risk. More importantly, the constant in this case was not found statistically significant and the inclusion of the market index excess return, again, did not affect each macro-variable's price, though market contained extra information.

To sum up, Clare and Thomas (1994) found that the portfolio formation matters when empirically estimating macroeconomic variables in an APT content. They estimated a large number of potential variables to reflect the "small, open UK economy" to finally conclude to a reduced model of variables.

Dolinar, Orsag and Suman (2015) examined the Chen et al.'s (1986) model on the Croatian stock market with several modifications for the observable factors due to constraints on the availability of data and found no supportive results. They argue that emerging capital markets

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[17] Many of these macro-variables were found insignificant and some of the estimated risk premia had changed sign.

like the Croatian, are specific and non-developed and thus there is a difficulty to apply such pricing models. They only found statistically significant premiums (at the 10% level) on a reduced form of the model, consisting of two factors: default premium and term structure but proxies for these two factors differ from what have extensively used in the literature. They defined default premium as the interest rate for short-term corporate loans and term structure as the difference between the 1-year and 3-month yields. An important aspect of their research however is that they have modified the second-pass series of Fama-MacBeth (1973) procedure with panel data analysis, allowing for tests on quarterly returns with a time-fixed effects model. Despite the many ambiguities in their methodology, a transformation of the conventional methodology into a panel data analysis has indeed many advantages (but also with some caveats). We discuss these advantages in the main body of our methodology in the following section as we have also modified the second-pass procedure to a panel form, though in a different manner.

Cochrane (2001) has shown that the Fama-MacBeth (1973) two pass procedure gives numerically equivalent estimates if a Pooled OLS regression is implemented in case where beta estimates do not vary throughout the sample period. In the regressions he suggests standard errors correcting for cross-sectional correlation assuming errors are not correlated across time, although he recognizes the latter assumption usually does not hold when pooled regressions are run in corporate finance topics. In our methodology we suggest Pooled GLS regressions allowing factor loadings values to vary during the testing period, as we observed this variation was significant in most cases.

Section 5. «Data and Methodology»

In this study we test whether certain observable factors affect stock prices in the US and specifically if they could serve as legitimate pervasive factors in a multifactor model derived by Arbitrage Pricing Theory. Our set of candidate factors includes four of the variables proposed by Chen et al. (1986) in their multifactor model, namely industrial production, inflation, changes of default premium and twists in the yield curve, and two factors we suggested could capture additional risks, these are policy-related economic uncertainty and developments in the US tech-sector. Thus, there are three main questions we try to answer through this study:

a) Do the four variables of Chen, Roll and Ross (1986) still count as pervasive forces in the US of 2005-2017, especially after a rigorous derivation of unanticipated components?
b) Do factors associated with the perception of policy uncertainty and unexpected technology developments have any additional explanatory power?
c) What if we change the securities' classification within the portfolios? Is the model still robust to different portfolio formations?

Most studies use a Fama and MacBeth (1973) variant two-step procedure to estimate the risk premia. In their first step, they implement time series regressions to derive the portfolio returns' sensitivities (betas) associated with each factor's realizations, as we do. In their second step, they run monthly cross-sectional regressions of portfolio returns on the estimated betas to derive the premia. All cross-sectionals will finally give a series of monthly premia and thus they estimate, with the provision of t-tests, the significance of each premia separately. We provide reasons to substitute all these cross-sectionals with a panel data analysis. By doing this we can estimate for several effects, we argue this method is applicable and more reliable when short periods are being tested, and more important, we can test both the significance of the premia and the multifactor model.

We have built two algorithmic codes to support this study. The first one (presented in Appendix A) constructs three types of portfolios, one where securities have been sorted by their market capitalization, one where securities have been arranged by their simple CAPM betas and one depending on their industry. The former two portfolios are rearranged per annum and per month respectively and the user specifies the number of portfolios. The second algorithm (presented in Appendix B) runs all time-series regressions (with a rolling window technique) of the first-pass methodology and produces a matrix of estimated betas which is applicable to panel data analyses. The user is flexible to set the initial estimation period (and thus the testing period over the entire sample period). With the provision of these two codes, one can easily test whether our results are reliable or even search for additional factors.

In our study we test for risk premia in the US stock markets within the period from January 2005 through December 2017 (entire testing period). Thus, our full sample period starts from January 2000 as the first five years of data (60 months) will be used as the initial estimation period to derive the beta estimates associated to the calendar year of 2005. We may describe the rolling-forward methodology of estimates in subsection 5.4.

5.1 Securities selection

We found series for 10,362 securities listed in either NASDAQ or NYSE via Thomson Reuters Datastream, but many of them did not have an appropriate number of data so we were enforced to reduce our sample. Another reason for doing so, was to make our data manageable. At first, we required each security has no missing observations within the period December 1999 – December 2017 and its industry not being unspecified. We then observed many misspecifications in the series of either adjusted prices or the market value of equity of many firms. To obtain a reliable sample of securities we tested for both outlying data in their prices and exposures to the market risk. Specifically, we performed two Grubb's "one-sided" tests in the adjusted price series. The first one detects any outliers on the maximum values, whilst the second on the minimum values, both at the 5% level of significance, and thus we could distinguish more easily the normal from non-normal series. It is important to mention that any outliers within specific months (i.e. minimum outliers during the financial crisis of 2007-2009) is not a problem. Intensive outliers observed on months of no interest though, may cause distortions on results. We also run simple CAPM regressions for all securities to remove outlying firms. The procedure we followed is quite complicated. For each security for the period between January 2000 and December 2004 we regressed its excess returns on S&P500 excess returns and derived the beta estimate. We then rolled-forward this period by one month (that is from February 2000 through January 2005) to derive a second beta estimate and repeated this procedure for the entire sample period. Consequently, for every security we obtained a series of beta estimates and thus could check for "outlying" securities in the sample, after calculating each series average, maximum and minimum values. We presume these two different tests are enough to distinguish the bad data and decided to remove these securities which could not fulfill our requirements, as they could distort our results. Our final sample consists of 1,161 securities, an adequate number compared to all relevant studies in our knowledge. For all securities we have calculated continuously compounded returns using adjusted monthly prices and dividends per share. Table 5.1 presents the number of selected securities per industry. We used the Industry names presented by Thomson Reuters Datastream (see third column), but for convenience we produced a code to name each industry (see second column).

Table 5.1

This table reports the number of securities per industry in the sample. Series of adjusted price per share, dividends per share and market capitalization were downloaded from Thomson Reuters (Datastream). A total of 1,161 stocks compose the sample. All series are end-of-month data for the period from December 1999 through December 2017. Thomson Reuters categorizes its securities into the following industries. A code of a maximum of 6 letters (column 2) was given for each industry for convenience in data processing. Unclassified stocks were not included in the sample.

	Code	**Industry**	**Securities**
1	AERDEF	Aerospace & Defense	13
2	ALTENE	Alternative Energy	0
3	AUTOMO	Automobiles & Parts	6
4	BANKS	Banks	278
5	BEVERA	Beverages	10
6	CHEMIC	Chemicals	20
7	CONSTR	Construction & Materials	18
8	ELCTCT	Electricity	31
9	ELCTNC	Electronic & Electrical Equipment	17
10	EQINVE	Equity Investment Instruments	129
11	FINSER	Financial Services (Sector)	26
12	FXLTEL	Fixed Line Telecommunications	5
13	FOODRU	Food & Drug Retailers	11
14	FOODPR	Food Producers	33
15	FOREST	Forestry & Paper	4
16	GASWAT	Gas, Water & Multiutilities	29
17	GENIND	General Industrials	18
18	GENRET	General Retailers	38
19	HEALTH	Health Care Equipment & Services	45
20	HSCONS	Household Goods & Home Construction	32
21	INDENG	Industrial Engineering	30
22	INDMET	Industrial Metals & Mining	2
23	INDTRA	Industrial Transportation	29
24	LEISUR	Leisure Goods	8
25	LIFEIN	Life Insurance	5
26	MEDIA	Media	20
27	MINING	Mining	4
28	MOBTEL	Mobile Telecommunications	2
29	NEQINV	Nonequity Investment Instruments	3
30	NLFINS	Nonlife Insurance	32
31	OILGAS	Oil & Gas Producers	34
32	OILEQP	Oil Equipment & Services	20
33	PERSGO	Personal Goods	21
34	PHABIO	Pharmaceuticals & Biotechnology	19
35	RESINS	Real Estate Investment & Services	12
36	RESINT	Real Estate Investment Trusts	70
37	SOFTCO	Software & Computer Services	19
38	SUPSER	Support Services	31
39	TECHAR	Technology Hardware & Equipment	9
40	TOBACC	Tobacco	4
41	TRAVEL	Travel & Leisure	24
		Entire Sample	**1,161**

5.2 Portfolios Formation

One of the most important aspects of this research, is our attempt to check the robustness of results when different techniques have been used to construct portfolios. Chen et al. (1986) and Chan et al. (1985) sorted securities based on their total market value at the beginning of each testable period and constructed 20 equally weighted portfolios. Chen and Jordan (1993) constructed industry portfolios and Clare and Thomas (1994) formed portfolios based on the securities' CAPM betas each year. We use three alternatives to construct portfolios.

Our first alternative consists of portfolios formation based on the firms' size. Quite similar to Chen et al. (1986), for the first calendar year in our sample (i.e. 2000), we ranked the securities in ascending order based on their market value of equity as reported at the end of previous year (i.e. December 1999) and then we constructed 30 equally weighted portfolios with approximately the same number of securities (see table 5.2 below) and calculated the monthly portfolio returns. We repeated this process each year in the sample and hence, have constructed series of returns for all the 30 portfolios which have reorganized their securities at the beginning of each calendar year. One could express his/her concerns however when this technique is implemented. Portfolio returns might be not synchronous to the constituent firms' size but we tested to rearrange securities in a monthly basis and the portfolio returns did not change much. We present the method of annual re-arrangement to make the results comparable with the findings of Chen et al. (1986) and Chan et al. (1985).

Our second technique consists of portfolios formation based on the securities' simple CAPM betas (see table 5.3 below). Unlike Clare and Thomas (1994) who only use 12 monthly observations each year on their regressions to get the beta time series, and hence enforcing the portfolios reorganized per annum, we followed a different approach. For the first 5 years of data (period between January 2000 and December 2004), we run a simple CAPM regression using the excess returns of each security and the excess returns of the S&P500 index[18] and estimated the beta coefficients. Then, we sorted all securities in ascending order based on their 'market' beta and formed 30 equally weighted portfolios with almost the same number of securities and calculated their monthly returns for the period of the first five years plus the next month (January 2005). Subsequently, we rolled forward the sample of 5 years by one month (i.e. from February 2000 through January 2005), estimated new 'market' beta coefficients for each security and sorted again the securities in ascending order based on their beta. Thus, we let portfolios reorganize their securities and estimated their returns for the next month (February 2005). Finally, we repeated this process for each of the following months in our sample until the securities' re-arrangement based on the last series of regressions (December 2012 – November 2017) give the portfolio returns for December 2017. With this procedure we allow the portfolios to change their constituent securities in a monthly basis whenever securities become more (or less) risky and use 60 observations for each regression (5 years, 12 months each). We preferred this method since we observed within-

[18] Series of end-of-month S&P 500 index were provided from Bloomberg Terminal (code: SPX Index). As a proxy for the risk-free rate to estimate excess returns, we obtained series of US Treasury Constant Maturity 3-Month (middle) rate from Thomson Reuters - Datastream (code: FRTCM3M).

year variations of risk exposures and thus allowing portfolios reorganize their securities per annum, the portfolios would not maintain their risk profiles. Furthermore, we presume the technique followed by Clare and Thomas (1994) could render beta estimates flawed as 12 observations are not always enough to obtain the securities attributes and thus the categorization could be spurious.

Lastly, the simplest is to rank the securities according to their industry (as reported in Thomson Reuters Datastream). As can be seen in table 5.1 however, many industries in our sample consist of only a few securities. Therefore, any expectations of having mitigated the problem of firm-specific errors would be exaggerated and thus, results based on this technique are not conclusive, but are only presented to lend support to the results of previous techniques. We required each industry in the sample to have at least 10 securities in order to regard it as a portfolio of stocks. As a consequence, not all securities in the sample have been tested using this technique. An interesting examination would be to corroborate that intra-industry effects are not priced by the markets systematically as investors, according to the theory can diversify these risks by investing in various sectors.

In Appendix A we present the description and the code of an algorithmic procedure we constructed to form the portfolios. This algorithm exploits the sample data to calculate the returns of each security and further produces three different types of portfolios (MVE-sorted, beta-sorted and industry portfolios). We hope the description will make this code user-friendly and may provide a useful tool as it lets the user intervene in several ways and adjust the code upon his needs.

In table 5.2 we provide some characteristics for the portfolios constructed based on the securities' firm size. MV1 is the portfolio consisting of securities with the smallest firms' size and MV30 is the portfolio of securities with the largest firms' size. The forth column contains the average monthly return for each portfolio when the full-sample period is considered, the fifth column contains the standard deviation of these returns and the sixth column, the coefficient of variation which is the ratio of standard deviation on average monthly returns. Each January all sample securities have been arranged in ascending order based on their market value of equity reported at the end of December of the previous calendar year and then they enter one of the 30 portfolios according to their rank. Thus, the composition of each portfolio changes every January within the sample period and portfolio returns calculation is based on the each-years' constituent securities returns using equal weights. As the table depicts, average returns series is not a monotonic function. We can see that the two extreme portfolios differ significantly comparing their average returns, but this is not the case for most of the portfolios. Reilly and Brown (2002) report small stocks outperform large capitalization stocks in the long run, but this does not hold for shorter periods. Indeed, as stocks are rearranged per annum based on their size, we cannot see their long-run performance. This method of forming portfolios did not achieve an adequate spread on returns across the portfolios as can be seen in Figure 5.1. Thus, we may not use these portfolios in our main tests, but rather, we may use them in the secondary series of tests to check if our results are robust.

Figure 5.1

The following scatter-plot depicts the average monthly returns (annualized) per portfolio arranged by the firm-size criterion. Returns were calculated for the entire sample period (Jan. 2000 – Dec. 2017). Securities re-arrangement into the 30 portfolios occurred in an annual basis. Y axis contains portfolio returns. X axis contains the 30 portfolios in ascending order based on their constituent securities' market capitalization. Thus, the first portfolio consists of securities with the smallest market capitalization and the 30th portfolio consists of securities with the highest market capitalization.

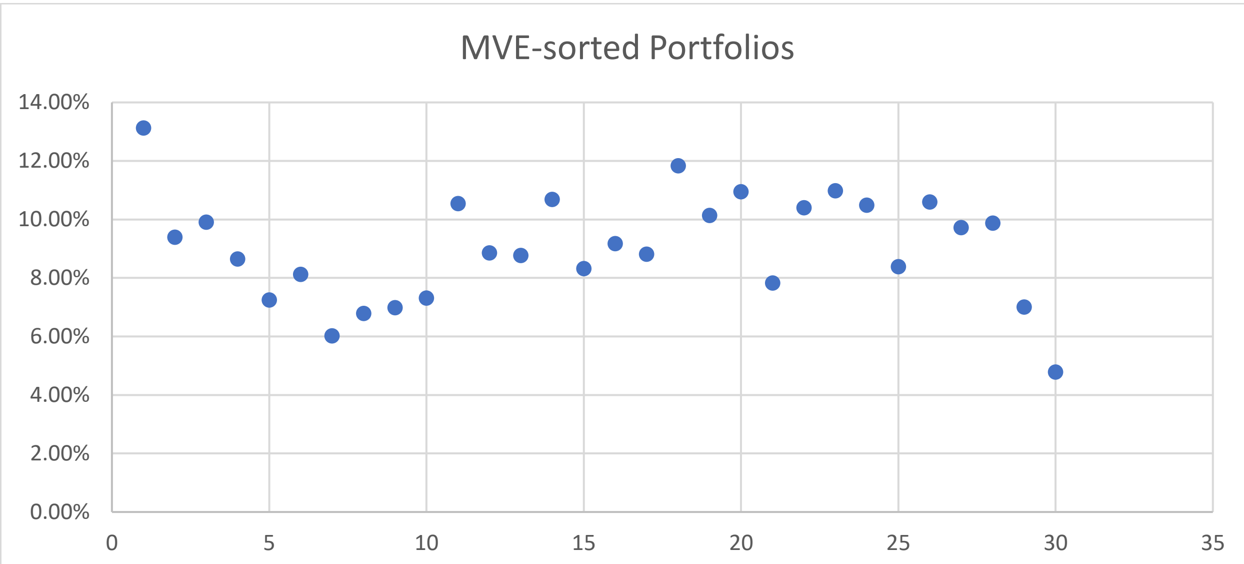

Table 5.3 gives the characteristics of portfolios arranged by the securities' exposure to market risk. Although the column of average returns per month does not reveal a monotonic pattern (something which has been also observed by Clare and Thomas (1994)), we observe consistent with the theory that on average, securities of which returns are more sensitive to the market risk compensate more their investors. Figure 5.2 depicts this relation. Obviously, this method has achieved a better spread on returns and thus will be used to derive our main findings. When we divided the entire period into subperiods we observed large deviations of these characteristics, especially before and after the financial crisis of 2007-2008. Many portfolios exposed large deviations on returns, and many had different return patterns after the crisis. We also observed these deviations on the MVE-sorted portfolios.

In table 5.4 we present the characteristics of portfolios arranged by their industry. Obviously, the composition of securities does not change through the entire period. In case where industry groups do not fulfill our requirements to have at least 10 stocks, they are not regarded as a portfolio. Thus, we have constructed 29 industry portfolios and the number of constituent securities varies significantly across groups, same as their average returns. Figure 5.3 depicts the annualized average monthly returns for each industry portfolio.

Figure 5.2

This scatter-plot depicts the average monthly returns (annualized) per portfolio arranged by the firms' exposure to market risk criterion. Returns were calculated for the entire sample period (Jan. 2000 – Dec. 2017). Securities re-arrangement into the 30 portfolios occurred in a monthly basis. Y axis contains portfolio returns. X axis contains the 30 portfolios in ascending order based on their simple CAPM beta estimation. Thus, the first portfolio consists of securities with the lowest beta estimates and the 30th portfolio consists of securities with the highest beta estimates.

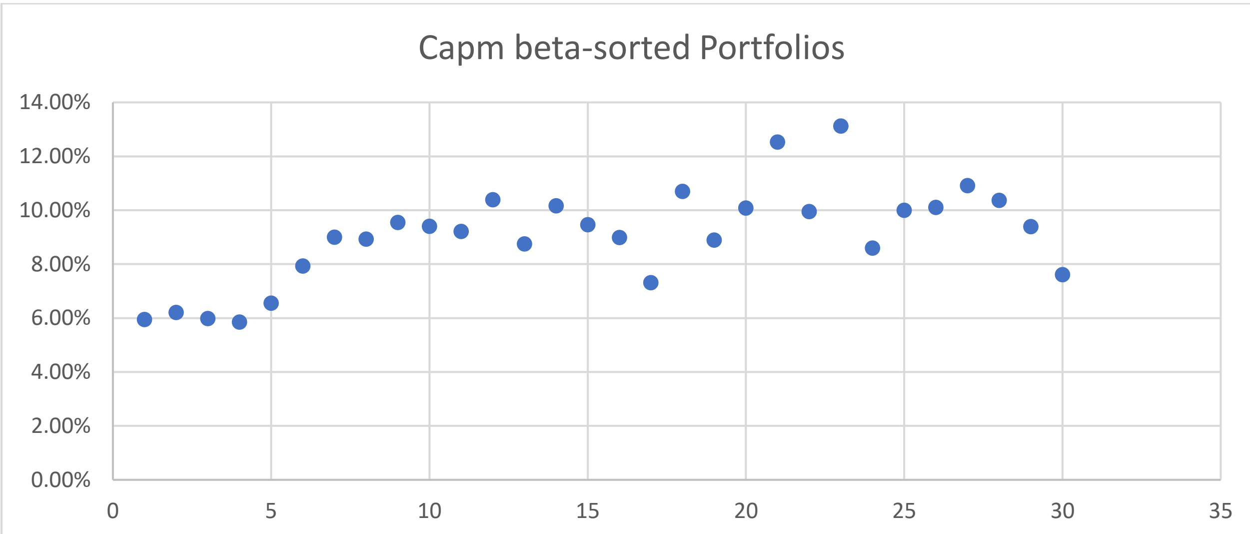

Figure 5.3

This scatter-plot depicts the average monthly returns (annualized) per industry portfolio. Returns were calculated for the entire sample period (Jan. 2000 – Dec. 2017). Securities were grouped into one of the 29 portfolios based on their industry and there is no re-arrangement during the entire sample period. Y axis contains portfolio returns. X axis contains the 29 portfolios in the same order as presented in table 5.4.

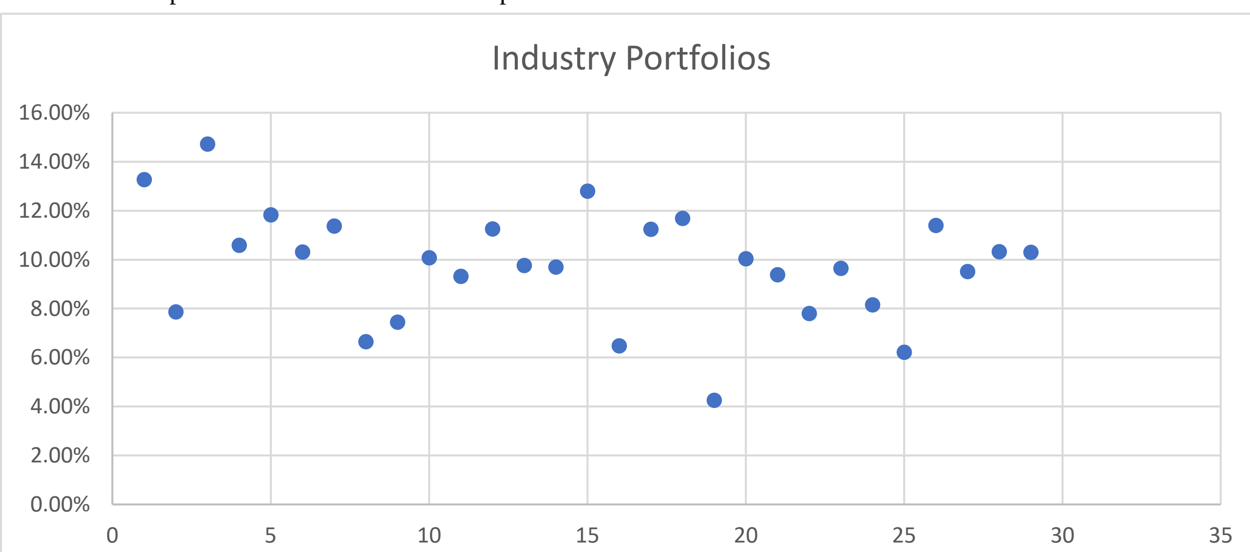

Table 5.2

This table reports the 30 portfolios of stocks arranged by the securities' Market Value of Equity (MVE). Every January in the sample, securities are classified by their MVE as reported at the end of previous calendar year (December). Thus, all portfolios are reconstructed per annum, but they maintain the same number of stocks. Column 2 presents the number of securities included in each portfolio. Average Market Cap per portfolio (in millions $) is reported in column 3, Average monthly portfolio returns for the entire sample period (2000-2017) in column 4, standard deviation of monthly returns in column 5 and the coefficient of variation in the last column. Coefficient of Variation is simply the St. Dev. divided by Avg Return. Portfolios are presented in ascending order and thus, MV1 (MV30) is the portfolio of stocks with the minimum (maximum) Market Cap.

Portfolio	Securities	Avg Market Cap (million US$)	Avg Return per month	St. Dev.	CV
MV1	39	7.48	1.03%	0.0346	3.35
MV2	39	16.17	0.75%	0.0260	3.46
MV3	39	24.46	0.79%	0.0265	3.35
MV4	39	33.25	0.69%	0.0264	3.81
MV5	39	44.31	0.59%	0.0285	4.87
MV6	39	56.59	0.65%	0.0243	3.72
MV7	39	71.71	0.49%	0.0287	5.88
MV8	39	93.13	0.55%	0.0310	5.65
MV9	39	119.29	0.56%	0.0300	5.32
MV10	39	151.76	0.59%	0.0313	5.31
MV11	39	190.85	0.84%	0.0338	4.03
MV12	39	240.98	0.71%	0.0352	4.97
MV13	39	313.18	0.70%	0.0391	5.56
MV14	39	405.36	0.85%	0.0402	4.73
MV15	39	520.4	0.67%	0.0408	6.10
MV16	39	667.37	0.73%	0.0416	5.67
MV17	39	847.59	0.71%	0.0423	5.98
MV18	39	1,068.12	0.94%	0.0431	4.60
MV19	39	1,309.06	0.81%	0.0436	5.40
MV20	39	1,596.78	0.87%	0.0413	4.75
MV21	39	1,955.69	0.63%	0.0436	6.91
MV22	38	2,469.09	0.83%	0.0402	4.86
MV23	38	3,110.90	0.87%	0.0419	4.80
MV24	38	4,055.26	0.83%	0.0402	4.81
MV25	38	5,438.51	0.67%	0.0370	5.49
MV26	38	7,800.71	0.84%	0.0382	4.53
MV27	38	11,515.11	0.78%	0.0389	5.01
MV28	38	17,252.37	0.79%	0.0380	4.82
MV29	38	30,158.43	0.57%	0.0397	7.01
MV30	38	109,575.93	0.39%	0.0364	9.33

Table 5.3

This table reports the 30 portfolios of stocks arranged by the securities' Simple CAPM Beta. For every security in the sample, an OLS time-series regression of monthly excess returns to S&P500 monthly excess returns was run for the first five years (2000-2004) and derived the beta coefficient. Then, all securities were sorted based on their beta coefficient and entered one of the 30 portfolios and monthly returns were estimated from Jan 2000 through Jan 2005. Thereafter, using a rolling window technique, securities were sorted again based on new beta estimates to let for a portfolio re-arrangement and portfolio returns were calculated for Feb 2005. The same procedure was repeated to derive series of portfolio returns for the entire sample period. Thus, all portfolios are reconstructed per month, except for the first 60 months, but they maintain the same number of stocks. Column 2 presents the number of securities included in each portfolio. Average beta per portfolio is reported in column 3, Average monthly portfolio returns for the entire sample period (2000-2017) in column 4, standard deviation of monthly returns in column 5 and the coefficient of variation in the last column. Coefficient of Variation is simply the St. Dev. divided by Avg Return. Portfolios are presented in ascending order and thus, BET1 (BET30) is the portfolio of stocks with the minimum (maximum) exposure to market risk.

Portfolio	Securities	Avg Beta	Avg Return per month	St. Dev.	CV
BET1	39	-0.11	0.48%	0.0248	5.14
BET2	39	0.01	0.50%	0.0203	4.04
BET3	39	0.07	0.49%	0.0196	4.04
BET4	39	0.13	0.47%	0.0207	4.36
BET5	39	0.18	0.53%	0.0222	4.18
BET6	39	0.24	0.64%	0.0208	3.26
BET7	39	0.29	0.72%	0.0245	3.40
BET8	39	0.35	0.72%	0.0247	3.46
BET9	39	0.39	0.76%	0.0259	3.39
BET10	39	0.44	0.75%	0.0269	3.57
BET11	39	0.49	0.74%	0.0295	4.00
BET12	39	0.53	0.83%	0.0289	3.50
BET13	39	0.58	0.70%	0.0308	4.39
BET14	39	0.62	0.81%	0.0328	4.04
BET15	39	0.66	0.76%	0.0337	4.45
BET16	39	0.70	0.72%	0.0342	4.76
BET17	39	0.74	0.59%	0.0391	6.63
BET18	39	0.78	0.85%	0.0364	4.28
BET19	39	0.83	0.71%	0.0366	5.13
BET20	39	0.87	0.80%	0.0384	4.78
BET21	39	0.92	0.99%	0.0392	3.97
BET22	38	0.96	0.79%	0.0400	5.05
BET23	38	1.01	1.03%	0.0422	4.09
BET24	38	1.07	0.69%	0.0442	6.41
BET25	38	1.13	0.80%	0.0466	5.85
BET26	38	1.19	0.81%	0.0505	6.27
BET27	38	1.27	0.87%	0.0512	5.91
BET28	38	1.36	0.83%	0.0536	6.49
BET29	38	1.47	0.75%	0.0552	7.35
BET30	38	1.71	0.61%	0.0626	10.22

Table 5.4

This table reports the 29 portfolios of stocks arranged by industry. Each security was grouped into one of the portfolios by its industry criterion and every portfolio maintain the same securities throughout the entire sample period (2000 - 2017). To consider an industry as a portfolio we required a minimum of 10 securities to represent this industry in the sample. Thus, not all securities were included into portfolios. From the total of 1,161 securities, a number of 1,109 were finally included in one of the 29 portfolios. Column 2 reports the industry code as presented in table 5.1. Column 3 presents the number of securities included in each portfolio. Average monthly portfolio returns for the entire sample period (2000-2017) is given in column 4, standard deviation of monthly returns in column 5 and the coefficient of variation in the last column. Coefficient of Variation is simply the St. Dev. divided by Avg Return.

	Portfolio	Securities	Avg Return per month	St. Dev.	CV
1	AERDEF	13	1.04%	0.0448	4.30
2	BANKS	278	0.63%	0.0294	4.64
3	BEVERA	10	1.15%	0.0428	3.72
4	CHEMIC	20	0.84%	0.0416	4.95
5	CONSTR	18	0.94%	0.0459	4.91
6	ELCTCT	31	0.82%	0.0341	4.15
7	ELCTNC	17	0.90%	0.0487	5.40
8	EQINVE	129	0.54%	0.0296	5.52
9	FINSER	26	0.60%	0.0410	6.83
10	FOODRU	11	0.80%	0.0397	4.94
11	FOODPR	33	0.74%	0.0326	4.37
12	GASWAT	29	0.89%	0.0308	3.45
13	GENIND	18	0.78%	0.0468	6.01
14	GENRET	38	0.77%	0.0470	6.08
15	HEALTH	45	1.01%	0.0399	3.96
16	HSCONS	32	0.52%	0.0445	8.50
17	INDENG	30	0.89%	0.0546	6.13
18	INDTRA	29	0.93%	0.0514	5.55
19	MEDIA	20	0.35%	0.0432	12.41
20	NLFINS	32	0.80%	0.0397	4.96
21	OILGAS	34	0.75%	0.0568	7.57
22	OILEQP	20	0.63%	0.0624	9.94
23	PERSGO	21	0.77%	0.0447	5.81
24	PHABIO	19	0.66%	0.0499	7.61
25	RESINS	12	0.50%	0.0415	8.25
26	RESINT	70	0.90%	0.0484	5.36
27	SOFTCO	19	0.76%	0.0494	6.50
28	SUPSER	31	0.82%	0.0450	5.47
29	TRAVEL	24	0.82%	0.0426	5.20

5.3 Explanatory Variables

In this subsection we describe the variables we worked on as proxies for pervasive influences to finally construct series of the factor realizations and test whether they carry risk premiums in the US stock markets. In our analysis we need monthly series of realizations for the period from 2000 through 2017. We have already presented in section 4 the six candidate factors we are interested to test. These are industrial production growth, inflation, changes of default premium, shifts in the slope of the yield curve, policy-related economic uncertainty and developments in technology sector. A large body of research has long tested whether the first four variables carry risk premiums. Chen et al. (1986) include them in their arbitrage pricing model. Recent literature also suggests the latter two variables are inherent to risk premiums in the market. But does their inclusion really improve the pricing model of the four initial variables? Technology related factor for instance is correlated with industrial production and policy uncertainty with the two bond-related factors respectively. It could thus be the case that the tech-growth and policy uncertainty do not contain information that the four-factor model does not capture, and vice versa, or the first four variables could no longer predict stock prices.

Furthermore, in the previous section we provided evidence that the method of *first differences* seems not an appropriate method to derive the factors as in most cases, severe serial correlations are presented, making the variables in some extent predictable. Recall that in a multifactor model emerged from Arbitrage Pricing Theory, candidate factors should be mean zero serially uncorrelated variables. Factor realizations should also be uncorrelated across-factors, a condition which can be relaxed. In any case however, they should not expose severe multicollinearity problems. We provided evidence that autoregressive models, or even better, Kalman filtering techniques should be used to isolate unanticipated movements. The latter are closer to EMH since they do not allow for systematic errors in expectations. In our study, we use the residuals of ARMA models to derive the unanticipated components[19] of the macroeconomic variables (i.e. factor realizations) with the provision of Gretl. Gretl reports ARMA models have been estimated using a Kalman filtering technique (exact maximum likelihood estimators) behind the scenes. Clare and Thomas (1994) used simple autoregressive models and claim to have carefully examined the residuals to ensure there are no systematic errors. We found however residual lags (Moving Average) contain information on the models, and since we should produce serially uncorrelated factors, we considered both autoregressive and moving average in this process.

Following, we give a brief description of the proxies we used as the candidate factors in our models and how did we derive unanticipated components (i.e. shocks) of the initial variables.

Industrial Production Growth

The Industrial Production index is compiled each month as a measurement of short-term changes in industrial output. Series for month-over-month changes in the US Industrial Production Index

[19] In another attempt which is not presented in this study, we tried to derive realizations of the factors from the residuals of VAR models, though serial correlation problems revealed and decided to exclude this technique.

were found from Bloomberg Terminal (code: IP CHNG:IND). Monthly growth rate of this index (denote it as PROD) can be used as an indicator of growth in the US industry. But since a portion of the growth rate is predictable, the variable could not enter the pricing model as a legitimate candidate APT factor. We tried out several combinations of orders and found out that an ARMA(2,2) model could isolate expected growth of PROD from its total per month growth in our sample. Let expectations about industrial production growth at the end of month t, given any information through the end of month t-1, be described by the following relationship:

$$\boldsymbol{E}[\mathbf{PROD}_{\boldsymbol{t}} | \, \mathbf{t-1}] \triangleq \boldsymbol{\gamma}_{\boldsymbol{o}}^{\boldsymbol{PROD}} + \sum_{\boldsymbol{i=1}}^{\mathbf{2}} \boldsymbol{\varphi}_{\boldsymbol{i}}^{\boldsymbol{PROD}} \, \boldsymbol{PROD}_{\boldsymbol{t-i}} + \sum_{\boldsymbol{i=1}}^{\mathbf{2}} \boldsymbol{\theta}_{\boldsymbol{i}}^{\boldsymbol{PROD}} \, \boldsymbol{\varepsilon}_{\boldsymbol{t-i}}^{\boldsymbol{PROD}} \qquad (5.1)$$

where γ_o is a constant parameter, φ_i's are the AR coefficients and θ_i's are the MA coefficients. Thus, the discrepancy between expectations and actual growth rate should serve as shocks on industrial production growth:

$$\boldsymbol{UIP}_{\boldsymbol{t}} = \mathbf{PROD}_{\boldsymbol{t}} - \boldsymbol{E}[\mathbf{PROD}_{\boldsymbol{t}} | \, \mathbf{t-1}] \qquad (5.2)$$

Since industrial production is a *coincident* index, and returns on stocks are *leading* indicators, any relationship among the two variables should exist with lagged return values. The index however is announced to investors in a later time and since we are interested to test how they react to shocks (that is, when realizations of this index differ from their expectations) we should take into account any delays (lags) in the announcements. For this reason, we regressed S&P500 returns on the unanticipated components of the industrial production growth and found that by leading its values by one month, series were not significant. In contrast, lags of the series by one and two months were significant at the 1% level[20]. We finally, decided to lag this series by one month only because we wanted to make the series as much more contemporaneous.

Inflation

As a proxy for inflation, we used the monthly growth rate of Consumer Price Index as presented in formula (4.3) in Section 4, that is:

$$\mathbf{INF}_{\boldsymbol{t}} = \mathbf{ln}(\boldsymbol{CPI}_{\boldsymbol{t}} / \boldsymbol{CPI}_{\boldsymbol{t-1}}) \qquad (4.3')$$

where CPI_t is the value of Consumer Price Index at the end of month t. Logarithmic differences denote the growth rate of prices or alternatively inflation. Seasonally adjusted CPI (all urban items) series were available from Thomson Reuters (Datastream) (code: USCONPRCE). To distinguish the unexpected components of the series, we found that an ARMA(3,4) was appropriate. Let,

[20] Significant lags were found with a VAR model where the appropriate number of lags was estimated by the AKAIKE criterion.

expectations about monthly inflation at the end of month t, given its values up until the end of month t-1, be described by the following equation:

$$\boldsymbol{E}[\mathbf{INF}_t|\ \mathbf{t-1}] \triangleq \boldsymbol{\gamma_o^{INF}} + \sum_{i=1}^{3} \boldsymbol{\varphi_i^{INF} INF_{t-i}} + \sum_{i=1}^{4} \boldsymbol{\theta_i^{INF}\ \varepsilon_{t-i}^{INF}} \tag{5.3}$$

From equation 4.2 we can derive unanticipated inflation as:

$$\boldsymbol{UINF_t} = \mathbf{INF}_t - \boldsymbol{E}[\mathbf{INF}_t|\ \mathbf{t-1}] \tag{4.2′}$$

Following the same arguments as with industrial production we could use a one-month lag of this series but found the explanatory power of inflation shocks was reduced and thus decided to use the contemporaneous shocks, as the previous studies did.

Term Structure

As a proxy for the slope of yield curve we used the spread between two yields: the 10-year Treasury constant maturity yield minus the 3-month Treasury constant maturity yield. End-of-month series were found from the Federal Reserve Bank of St. Louis (code: T10Y3M) and are reported to be not seasonally adjusted, though we tested for seasonality and found no effect[21]. To derive series for shifts in the slope of yield curve we simply obtained the first-difference of the spread series:

$$\boldsymbol{\Delta}\mathbf{TERM}_t = \boldsymbol{TERM_t} - \boldsymbol{TERM_{t-1}} \tag{5.4}$$

where,

$$\mathbf{TERM}_t = \mathbf{GOV\ YIELD}_t^{10Y} - \mathbf{GOV\ YIELD}_t^{3M} \tag{5.5}$$

First difference of the spreads also made the series stationary. The crucial point that stationary series enter in an autoregressive model, to derive their unanticipated components has already raised by Priestley (1996). Clare and Thomas (1994) used a similar series in the UK in *levels* and claim to have found no significant lags.

Default Premium

As a proxy for the default premium, we found a series of Moody's Seasoned Baa Corporate Bond Yield relative to Yield on 10-year Treasury Constant Maturity from the Federal Reserve Bank of St. Louis (code: BAA10Y). Series had not been adjusted for seasonality, but we tested and found

[21] To test for seasonality, we regressed the series with periodic dummies and only found the constant coefficient as statistically significant. F-statistic with 11 and 204 degrees of freedom was estimated to be .088971 (p-value .999950). Hence, we cannot reject the null hypothesis that the coefficients of dummy variables are not statistically different from zero. Test statistic for each coefficient was also statistically insignificant for all the conventional levels (10%, 5%, 1%) except for the intercept (test statistic 6.904) but the intercept does not indicate seasonality.

no seasonal effect[22]. We are interested to extract monthly changes of the above premium and hence we have used the first differences of this spread:

$$\boldsymbol{\Delta}\mathbf{DEF}_t = \boldsymbol{DEF_t} - \boldsymbol{DEF_{t-1}} \tag{5.6}$$

where,

$$\mathbf{DEF}_t = \mathbf{CORP\ YIELD}_t^{Baa} - \mathbf{GOV\ YIELD}_t^{10Y} \tag{5.7}$$

Yields of the spread are measured at the end-of-month t and $\Delta\mathrm{DEF}_t$ is the month-over-month change of the corporate spread. ΔDEF series did not meet the three criteria to regard it as a legitimate candidate factor and thus, unexpected movements of this spread were estimated as the residuals of an ARMA(3,3) model. That means, expectations about default spread movements could be described, ex post, by the following relationship:

$$E[\Delta\mathrm{DEF}_t |\ \mathrm{t}-1] \triangleq \gamma_o^{\Delta DEF} + \sum_{i=1}^{3} \varphi_i^{\Delta DEF} \Delta DEF_{t-i} + \sum_{i=1}^{3} \theta_i^{\Delta DEF}\ \varepsilon_{t-i}^{\Delta DEF} \tag{5.8}$$

Thus, unexpected movements are simply the difference between actual changes and expected changes of the yield spread:

$$UDP_t = \Delta\mathrm{DEF}_t - E[\Delta\mathrm{DEF}_t |\ \mathrm{t}-1] \tag{5.9}$$

Intensity of Policy Uncertainty

As a proxy for policy uncertainty in the US, we used the well-known EPU index of Baker, Bloom and Davis (2016)[23]. The higher the index value, the more the uncertainty in the US due to policy-related affairs. First difference of this monthly series should serve as a proxy for changes in the "levels" of uncertainty. We used log differences of the index to see how stock market reacts in percentage changes of the value of index (denote it as EPUG). Hence, positive (negative) changes are an indication of increasing (mitigating) uncertainty.

$$\mathrm{EPUG}_t = \ln(EPU_t / EPU_{t-1}) \tag{5.10}$$

To make the series unpredictable we used the residuals of an ARMA(3,3) model. Thus, if:

$$E[EPUG_t |\ \mathrm{t}-1] \triangleq \gamma_o^{EPUG} + \sum_{i=1}^{3} \varphi_i^{EPUG} EPUG_{t-i} + \sum_{i=1}^{3} \theta_i^{EPUG}\ \varepsilon_{t-i}^{EPUG} \tag{5.11}$$

then,

$$UEPU_t = EPUG_t - E[EPUG_t |\ t-1] \tag{5.12}$$

[22] Similar to footnote (21), we tested for seasonal effects and the F-statistic with 11 and 204 degrees of freedom was .152923 (p-value .999279). Hence, we cannot reject the null hypothesis that the coefficients (except for the intercept) equal to zero. Test statistic for each dummy coefficient was also statistically insignificant for all the conventional levels (10%, 5%, 1%).

[23] Series were available from http://www.policyuncertainty.com.

Though there is no "economic rationale" to isolate expectations about future uncertainty, we were "enforced" to use such an ARMA model, only because EPU series were not serially uncorrelated and thus, could not enter the model. Residuals of this ARMA(3,3) model on the other hand meet the prerequisites. Since references such "unexpected uncertainty" make no sense at all, we use this variable as a proxy to capture intensity of policy uncertainty regardless the source. Thus, it could be monetary, government, tax policies, etc., that cause the economic environment more or less uncertain. We could also treat this variable as an unobserved factor but due to the fact that the largest portion of this index is news-based, we may claim, in an extent this index captures investors' perception about uncertainty. This uncertainty is related to current and future policy affairs.

Developments in Tech-sector

As a proxy for the developments in the US tech-sector we used the San Francisco Tech Pulse Index which can be thought as a summary statistic of the health of IT sector. The higher its values the strongest the prospects in this sector. The Federal Reserve Bank of San Francisco announces its values and seasonally adjusted end-of-month series were available from the Federal Reserve Bank of St. Louis (code: SFTPINDM114SFRBSF). We used logarithmic differences of these series as a proxy for the monthly growth rate of technology sector. That is:

$$\mathbf{TECHG}_{\boldsymbol{t}} = \mathbf{ln}(\boldsymbol{TECH_t} / \boldsymbol{TECH_{t-1}}) \tag{5.13}$$

To isolate, ex post, expectations about tech-sector monthly growth rate we implemented an ARMA(4,5) model. Thus, if we let:

$$\boldsymbol{E[TECHG_t |}\, \mathbf{t-1}] \triangleq \boldsymbol{\gamma_o^{TECHG}} + \sum_{i=1}^{4} \boldsymbol{\varphi_i^{TECHG}\, TECHG_{t-i}} + \sum_{i=1}^{5} \boldsymbol{\theta_i^{TECHG}\, \varepsilon_{t-i}^{TECHG}} \tag{5.14}$$

then,

$$\boldsymbol{UTG_t} = \mathbf{TECHG}_{\boldsymbol{t}} - \boldsymbol{E[TECHG_t |\, t-1]} \tag{5.15}$$

By using ARMA models to isolate estimations about shocks on the variables, an assumption that agents use these models to predict, ex ante, movements of the corresponding variables and that coefficients of these models remain constant across-time is implied. ARMA models require stationary series and thus, before extracting the unanticipated components all series should be tested for the presence of a unit root. As it is shown in Panel A of table 5.5, we implemented two unit-root tests for each variable, the first one is *Zivot-Andrews* and the second is *Augmented Dickey and Fuller GLS* test. In case where these tests gave controversial results, we implemented additional tests, but these were quite weak. An advantage of the Zivot-Andrews test is, it considers potential structural breaks when identifying the presence of a unit root process. Null hypothesis for both tests is, series is not stationary. Recall, at this point, tests are implemented for the initial variables, where their expected values are not (necessarily) subtracted. These variables are *PROD*, *INF*, *ΔDEF*, *ΔTERM*, *EPUG* and *TECHG*. Obviously, all series were stationary at the 1% level of significance or at most at 5%, except for *TECHG* of which the first test estimated a unit root process at all conventional levels of significance, whilst the second test found this series stationary at the 1% level of significance. We performed a Philips Perron test for *TECHG* and the p-value was .0176. Hence, there is an indication that the alternative hypothesis of a stationary process holds. This is quite encouraging since if we were not able to reject null hypothesis, we would have to treat series as taking the first differences which would change the interpretation of our variables in the model.

Since there are strong indications our series are stationary, we can now turn to extract the unanticipated components of the series. A remarkable question however is how many orders of lags should enter the ARMA models? When presented the final form of all formulas to extract the factors (above) we set specific orders for each variable but did not make further justifications. As we may show latter on, we selected these specific orders because they made these variables serially uncorrelated. Autocorrelation Functions (ACF) and Partial Autocorrelation Functions (PACF) provide a plain guide to choose for the appropriate number of lags for an AR or a MA process. When modeling an ARMA process though, the appropriate combination of orders is not easily revealed. There is no clear suggestion about which ARMA model describes better the agents' expectations about a stochastic variable since each variable has a different pattern and this pattern, in most cases, changes over time. We preferred to use ARMA models though, since simple AR models with many lags insisted displaying serially correlated residuals which would violate what APT predicts.

In Panel B of table 5.5 we provide the PACF of 14 (monthly) lags for each of the six variables to have a sense of the appropriate number of orders. We have also assessed PACF for a greater number of lags, as well as ACF functions but the results are not presented. Except for *ΔTERM*, all variables displayed significant lags which means past values could forecast the current value of the variable and thus we had to extract the unanticipated components of these series. *ΔTERM* displays only a marginally significant lag at the 5% level for the eighth month, whilst the Box-Pierce Q-statistic for the first eight lags is 9.08 (p-value: .335) indicating no significance. Recent past values could not forecast its current value and thus we could consider that the yield spread on long-term minus short-term treasuries follows a random walk process. This is equal to saying that the first difference of this spread (i.e. *ΔTERM*) is already unpredictable and could serve as a candidate factor. Recall that previous studies tested this spread at levels.

For each variable, except for *ΔTERM*, we tried out several ARMA(p,q) models for different p and q lags and chose this model with the combination of as-minimum-as-possible p and q's of which residuals are serially uncorrelated at the 5% level of significance. Whenever residuals were autocorrelated we had to test ARMA models with different orders only to conclude to the parsimonious models we have already described above when introduced the variables. The derived factors are then, unexpected growth of industrial production (UIP), unanticipated inflation (UINF), unanticipated movements of default spread (UDP), shifts in the slope of the yield curve (ΔTERM), intensity of policy uncertainty (UEPU) and unexpected developments of tech-sector (UTG). In table 5.6 we provide evidence that series of these six variables could be tested as factor realizations in an APT model as they are mean zero, serially uncorrelated white noise processes and they are not severely correlated to each other.

Panel A of table 5.6 depicts the correlation among the six candidate factors. Obviously, there is no strong indication of the presence of multicollinearity in our data as the factors are far from perfectly correlated. The most correlated variables are *UEPU* and *UDP*. We find this correlation reasonable as both variables reflect uncertainty. The latter measures intensity of uncertainty in the economy as perceived in the bond markets, where investors require more compensations when corporate bonds' probability of default increases. Since variables are not displaying severe correlation, it is interesting to see whether a variable provides additional information with respect to the other. *UDP* is also negatively correlated with *ΔTERM* which makes sense since both variables contain the yield of the 10-year government bond. Furthermore, *ΔTERM* is negatively related to *UIP* due to delays on announcements of the later. Term structure is a leading indicator of future growth rate of output whilst industrial production captures current growth rates of industrial output. At peaks (troughs) of business cycles we may expect positive (negative) growth of announced IP and negative (positive) growth of long-term rates. In Panel B of table 5.6 values of Variance Inflation Factors have been estimated on a regression of S&P500 excess monthly returns with monthly realizations of the 6 candidate factors. VIF values are almost 1 indicating no multicollinearity on explanatory variables. On the same regression we derived collinearity diagnostics of the Belsley-Kuh-Welsch test (not presented here) and again found no collinearity. If we were facing multicollinearity problems, then the coefficients would remain unbiased, but the coefficients' standard errors would be large, imposing an error of type II[24]. This type of error would weaken our results, making it harder to find priced factors.

Series are also mean zero in the sample as residuals of ARMA models. Assuming *TERM* is a random walk, then *ΔTERM* is the residuals of an AR(1) process with $\rho=1$ of *TERM* series. What remains to assess whether the six factors could be tested as legitimate factors is to corroborate that past values cannot predict the current ones. In Panel C of table 5.6 we present the PACF of the six factors for 14 lags. Obviously, the PACF of *ΔTERM* is not presented as its values are shown in Panel B of table 5.5. Apparently, only *UINF* had a significant lag at the 12^{th} month and *UTG* at the 11^{th} month but both lags were significant at the 10% level[25]. We can estimate these lags to be negligible and therefore conclude we have (econometrically) removed agents' expectations of these series. In the last two rows we present the Q statistic along with the p-value of the Box-Pierce test for the first 14 lags. Under the null hypothesis, series is serially uncorrelated. All Q-statistics are low enough. Time series graphs related to the candidate factors for the entire sample period are given in Appendix C.

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[24] Error of type II occurs when we fail to reject the Null Hypothesis, but Null Hypothesis is false.

[25] Attempts to remove these two lags when running ARMA(p,q) models with an increased number of orders (p and q) turned to be unprofitable. We presume though these lags do not affect the legitimacy of testing the series as factors as their level of significance is 10%, especially when compared to previous researches in this area where the identity of non-serial correlation is being contaminated in most cases.

Table 5.5

This table reports two stationarity tests and a partial autocorrelation function for six variables, namely industrial production growth (PROD), inflation (INF), monthly movements of default spread (ΔDEF), monthly shifts in the slope of the yield curve (ΔTERM), intensity of policy uncertainty (EPUG) and technology growth (TECHG). If series are stationary, they can enter an ARMA model in order to extract the residuals as a proxy for unexpected components (i.e. factors). With the provision of Autocorrelation Functions (ACF) and Partial Autocorrelation Functions (PACF) we can estimate whether a series is (econometrically) unpredictable and have a sense of the appropriate number of orders (p and q) in ARMA(p,q) models. In this table ACF is not presented due to space constraints.
In Panel A, test statistics are presented for two stationarity tests, namely, *Zivot Andrews* and *Augmented Dickey Fuller GLS*. Under the null hypothesis of both tests, series have a unit root. Critical values for Zivot Andrews test are: -4.82 at 10% level, -5.08 at 5% level and -5.57 at 1% level of significance. Critical values for ADF GLS test are: -2.57 at 10% level, -2.89 at 5% level and -3.48 at 1% level of significance.
In Panel B, the PACF of each variable is presented for 14 lags (months). Asterisks denote significant autocorrelations: (*) significant at the 10% level, (**) significant at the 5% level and (***) significant at the 1% level.

	Variables					
	PROD	**INF**	**ΔDEF**	**ΔTERM**	**EPUG**	**TECHG**
Panel A	**Unit Root Tests**					
Test	Test Statistics					
Zivot Andrews	-12.2721	-9.8363	-10.9347	-14.698	-17.7133	-4.2332
ADF-GLS	-3.3711	-9.42119	-10.3111	-3.10609	-17.4891	-3.88512

Panel B	**Partial Autocorrelation Functions**					
Lags						
1M	0.2592 ***	0.4244 ***	0.3249 ***	0.0510	-0.1886 ***	0.9390 ***
2M	0.2092 ***	-0.2298 ***	-0.1222 *	-0.0674	-0.2215 ***	-0.6952 ***
3M	0.2409 ***	0.0364	0.0748	0.1055	-0.2041 ***	0.3818 ***
4M	0.1958 ***	0.0365	0.0328	0.0510	-0.1431 **	-0.0266
5M	0.0288	-0.1322 *	0.0094	0.0047	0.0413	-0.1756 ***
6M	0.0374	0.0306	-0.1348 **	0.0317	-0.0211	-0.0502
7M	-0.1504**	-0.0281	0.0029	-0.0203	-0.1312 *	-0.0151
8M	-0.0577	-0.0879	-0.0331	0.1424 **	-0.1179 *	-0.038
9M	-0.0752	0.0197	-0.046	-0.0065	-0.0859	-0.0726
10M	-0.0468	0.1137 *	0.0145	-0.0057	0.0187	0.0245
11M	-0.054	-0.0433	0.0041	-0.0524	-0.0053	-0.0103
12M	-0.1057	-0.1914 ***	0.0733	0.0124	0.0409	0.0024
13M	-0.0183	0.0349	-0.1622 **	-0.0599	0.0223	0.0321
14M	-0.0042	0.0101	0.1085	0.0205	-0.0556	0.0313

Table 5.6

This table reports some characteristics of the six candidate factors. These factors are unexpected growth of industrial production (UIP), unanticipated inflation (UINF), unexpected movements of default premium (UDP), shifts in the slope of the yield curve (ΔTERM), unexpected movements (%) of EPU index (UEPU) and unanticipated developments of tech-sector (UTG). All candidate factors should meet three criteria: mean zero, serially uncorrelated and uncorrelated with the remaining factors. Except for ΔTERM, all factors have been derived by the residuals of ARMA models and thus are mean zero. ΔTERM is also a mean zero variable as it is the monthly difference of yields spread. To corroborate this statement, a simple test statistic for the entire sample period was -0.0246 (two tailed p-value 0.98). The remaining two criteria are related to Panels A-B.
Panel A presents the correlation matrix of the six factors. Correlation coefficients were estimated with monthly series of the factors for the entire sample period (2000-2017).
To corroborate there is no severe multicollinearity a regression of S&P500 monthly excess returns with the six factor' realizations was run and then estimated the Variance Inflation Factor (VIF). VIF values are presented in Panel B. Values above 10 may indicate collinearity problems. The minimum value is always 1.
In Panel C the Partial Autocorrelation Function (PACF) for 14 lags is shown for each factor to corroborate lagged values cannot predict the current one. One star (*) indicates significance at the 10% level. ΔTERM's PACF is not shown as it has already been presented in table 5.5. The last two rows are related to Box-Pierce Q-statistic and its p-value for the first 14 lags of each series. Under the null hypothesis, series are not autocorrelated.

			Candidate Factors			
	UIP	**UINF**	**UDP**	**ΔTERM**	**UEPU**	**UTG**
Panel A			**Correlation Matrix**			
UIP		0.0243	-0.1636	-0.2338	-0.0303	0.0840
UINF			-0.1176	0.1356	0.0177	0.0868
UDP				-0.1804	0.2577	-0.1454
ΔTERM					0.1668	-0.1115
UEPU						-0.0051
Panel B			**Variance Inflation Factor**			
Value	1.118	1.038	1.239	1.226	1.140	1.056
Panel C			**Partial Autocorrelation Functions**			
Lags						
1M	0.0187	-0.0026	0.0073	see table 5.5	0.0144	0.1117
2M	-0.0610	-0.0120	0.0390		-0.0499	-0.0139
3M	0.0281	-0.0008	0.0543		0.0072	0.0025
4M	0.0524	-0.0073	0.0185		0.0049	-0.0438
5M	-0.0394	-0.0819	0.0012		0.0648	0.0109
6M	0.0410	-0.0786	-0.0660		-0.0237	0.0061
7M	-0.0954	0.0557	-0.0268		-0.0675	0.0018
8M	0.0246	0.0040	-0.0551		-0.0484	0.0161
9M	0.0252	-0.1107	-0.0575		-0.0195	-0.0487
10M	0.0348	0.0215	0.0663		0.1117	-0.0012
11M	-0.0020	0.1018	-0.0656		0.0691	-0.1309*
12M	-0.0889	-0.1297*	0.0940		0.0304	-0.0582
13M	-0.0142	-0.0308	-0.1059		-0.0356	-0.0019
14M	-0.0195	-0.0583	0.0493		-0.0337	-0.0714
Box-Pierce Q statistic	**6.1727**	**13.8481**	**10.7002**	**10.3633**	**8.0739**	**10.4862**
[P-value]	[0.962]	[0.461]	[0.709]	[0.735]	[0.885]	[0.726]

5.4 Methodology

This subsection describes the main methodology we followed to test for priced factors affecting the US stock market returns, as well as how our procedure differs from several works implemented in the past.

Following the procedure of relevant studies, we used a variant of Fama and MacBeth (1973) technique to test for pervasive forces, which can be decomposed into two stages. The first stage consists of time series regressions to obtain the stock returns' sensitivities on the candidate factors (factor loadings) and the second stage, for which the literature has suggested cross-sectional regressions to test for risk premia, has altered to a panel data analysis. The analytic procedure is as follows:

1. We calculate monthly stock returns for each of the 1,161 securities for the entire sample period from January 2000 through December 2017.

2. We then group the securities into portfolios and obtain series of the monthly portfolio returns. At this point we use three different techniques to construct equally weighted portfolios, and thus we report three different assessments. On the first trial we use 30 portfolios, formulated according to the securities' exposure to market risk, on the second trial we test 30 portfolios arranged by the firm-size criterion and the last assessment is provided with 29 industry portfolios. These three techniques also differ each other on the frequency each portfolio has changed its composite securities over the entire sample period. We have already provided a detailed description of the procedure we followed to construct portfolios in subsection 5.2 and in Appendix A.

3. For the period between January 2000 and December 2004 (first 60 months in the sample) we regress portfolio returns on the factors' realizations to derive their beta coefficient estimates. Specifically, we run an OLS time-series regression for each portfolio where the dependent variable is its monthly excess returns and the explanatory variables are the derived factors, we argued earlier may affect returns. The model we constructed at this step is:

$$\boldsymbol{R_{pt} - R_{ft} = b_0 + \sum_{j=1}^{k} b_{pj} f_{jt} + e_{pt}} \tag{5.6}$$

for p=1, 2, …, P portfolios and j=1, 2, …, K factors, where:

$R_{pt} - R_{ft}$: Ex-post returns on portfolio p in excess of the risk-free rate[26] at the end of month t.
b_0: The constant coefficient which is assumed to represent the expected returns minus the

[26] As a proxy for the risk-free rate we obtained monthly series of annualized 3M TBill rate from Thomson Reuters (Datastream) and calculated a monthly equivalent as [(1+TBILL3M)^12] – 1.

risk free rate, that is the overall risk premium.
b_{pj}: The beta coefficient of the p^th^ portfolio returns on the j^th^ factor.
f_{jt} : (Unexpected) realizations of the j^th^ factor at the end of month t.
e_{pt}: The disturbance term, which is assumed to represent all diversifiable risks.

Notice that, since we have no idea what the actual set of factors is, any omitted variables will affect the constant coefficient and the disturbance term. Apparently when all the variables we have specified are included in the model, *k* takes the number of 6 and f_{jt}'s are the series of *UIP*, *UINF*, *UDP*, *ΔTERM*, *UEPU* and *UTG* (for different *j*'s). When a restricted model is used though, not all of the 6 variables are included in the model. Since we use returns in excess of the risk-free rate, the constant coefficient no longer represents the expected portfolio returns but the overall contribution of risk premia on expected returns. In other words, we have implicitly subtracted by both sides of equation the risk-free rate, allowing it to change each month.

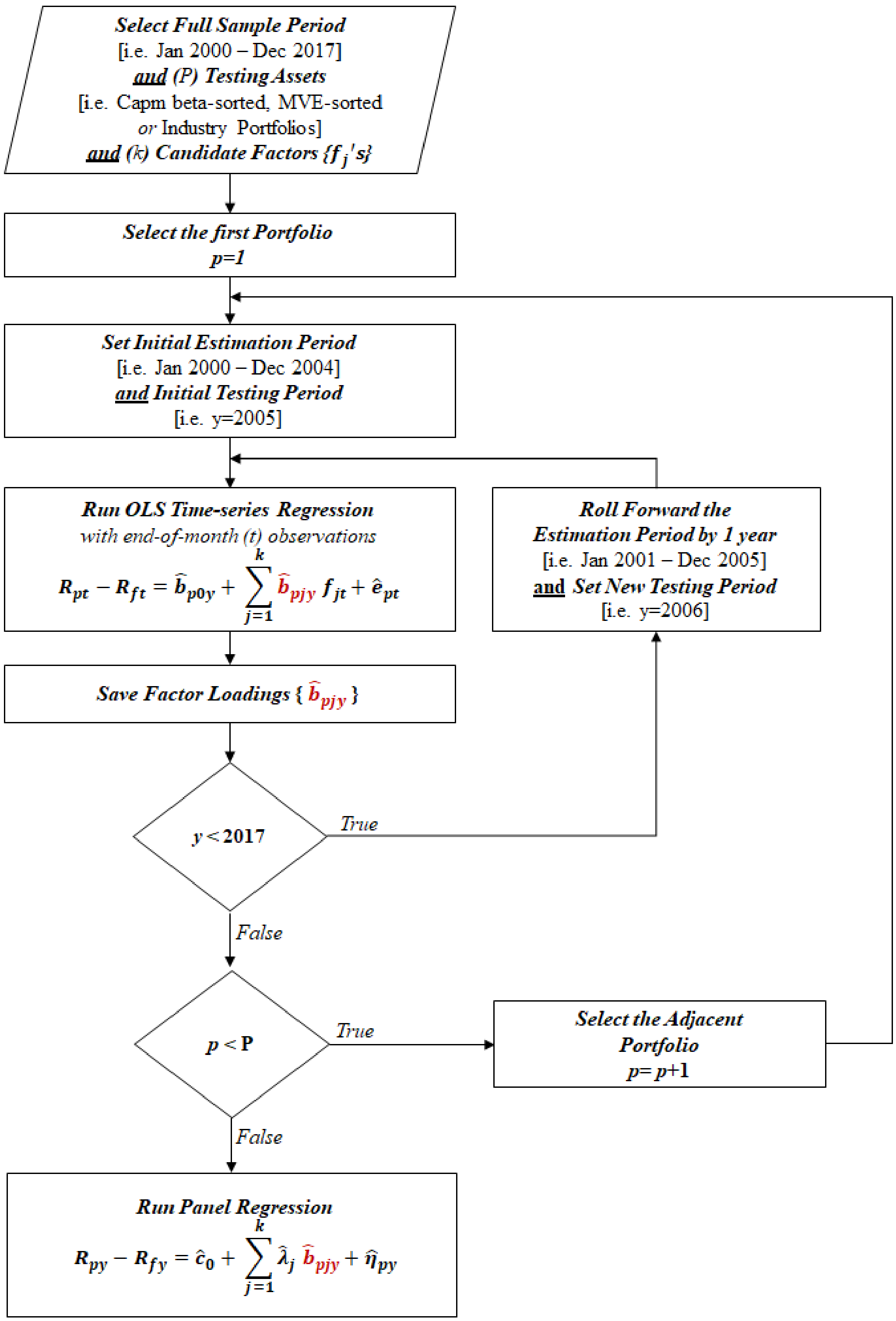
4. Having obtained the beta coefficients for each portfolio, the literature has suggested running 12 cross-sectional regressions of the portfolio returns from January 2005 through December 2005 on the above beta estimates and derive the risk-premia estimates (i.e. λ's). That is, for each *t* from January 2005 through December 2005 run a cross-sectional of the form:

$$R_{pt} = \lambda_{0t} + \sum_{j=1}^{k} \lambda_{jt}\, b_{pj} + \eta_{pt} \tag{5.7}$$

for p=1, 2, …, *P*, and *j*=1, 2, …, *K*. Researchers who run the above regressions had implicitly assumed that the portfolio sensitivities to each factor remain stable month-by-month over the calendar year. Unfortunately, this is not the case in most of the circumstances[27], but is an appropriate technique to measure the effects of the pervasive forces on portfolios with certain characteristics. Allowing betas change each month, when returns also change, we obstruct the model to detect properly any relationship between returns and risk. In contrast, with stable betas across the calendar year, we can observe more clearly the effect of the factors on returns. Thus, we roll forward the estimation period of step (3) by one calendar year, that is setting the period from January 2001 to December 2005, and run again the time series regressions of step (3). These new estimates will then be used in the next step to explain the actual portfolio returns of 2006. We repeat this process until the last estimation period is January 2012 to December 2016. The beta estimates of the last estimation period will be used to test the actual returns occurred in 2017, which is the last calendar year of the entire sample. The above repeated procedure results in time-series estimates of the $b_{pj}'s$ from 2005 through 2017. Figure 5.4 depicts this procedure. Obviously, these estimated parameters are to tested out-of-sample as the estimation period precedes the testing period.

[27] Rolling forward the period of step (3) by one month and running again the time-series regression, we observed that the beta estimates vary (in most of the cases significantly) month-by-month over the entire period.

Figure 5.4
The following chart-flow diagram depicts the rolling window procedure followed to estimate a series of factor loadings (beta coefficients) for every portfolio related to each factor to finally run regressions in a panel form.



Up to this point, steps 1 and 2 of this procedure were implemented with the provision of the algorithm presented in Appendix A. We have already described this procedure (see: subsection 5.2 and the description in *Appendix A*). Steps 3 and 4 were implemented with the provision of the second algorithm, which is presented in Appendix B.

5. Having the series of these betas, we can test for priced factors in panel regressions throughout several testing periods. The general form of the model in this stage is:

$$\boldsymbol{R_{py} - R_{fy} = c_0 + \sum_{j=1}^{k} \lambda_j \, b_{pjy} + \eta_{py}} \tag{5.8}$$

for *p*=1, 2, …, P where P is the number of Portfolios, *y*=1, 2, …, *Y* where *Y* is the number of total calendar years throughout the entire testing period and *j*=1, 2, …, *k*, where *k* is the number of observed factors. Furthermore:

$R_{py} - R_{fy}$: Ex post excess annual returns of portfolio p at the end of year y.
c_0: The constant coefficient which should ideally be statistically equal to zero, since we use portfolio returns in *excess* of the risk-free rate. Otherwise, we would simply expect it to represent the λ_0 as presented from theory.
b_{pjy}: The beta coefficient of p^{th} portfolio returns on the j^{th} observed factor derived by the 60 monthly observations prior to the calendar year *y*.
λ_j : The estimated annual risk premium relevant to the j^{th} observed factor.
η_{pt}: The residuals.

We could simply run monthly cross-sectionals with this rolling technique as the conventional literature has suggested, but there are many advantages when regressing in a panel form. At first, we derive our estimations by exploiting more observations. Following the conservative method of cross-sectionals in the second step of the Fama and MacBeth (1973) procedure one must derive time series for each λ_j and then perform a t-test to estimate whether this price is significantly different from zero. Recall that, previous works, such those of Chen et al. (1986) and Chan et al. (1985) obtained the series of monthly risk-premia by regressing (for each month) 20 portfolio returns on their factor loadings cross sectionally and then tested each series' significance separately by a t-test. There are many reasons to believe that 20 observations are not enough to produce reliable premia. Of course, one could simply form an adequate number of portfolios to mitigate this problem, but in this case, there might be concerns about the diversifiable risks inherent to portfolio returns, as each portfolio will then contain a smaller number of securities. For instance, Clare and Thomas (1994) used 56 portfolios on their tests but each comprising of only 15 stocks, a low enough number to ensure no diversifiable errors.

In addition, having obtained the monthly premia for each risk, a test-statistic on each series' premia requires more than 30 observations to give reliable estimates. We shall not expect, of course, these series to be random. Thus, one is ought to test for significant prices only if the sample consists of a large number of observations across time. During this period a variable could turn to be insignificant if investors in general changed their perceptions about which variables affect stock returns and could require compensations for different risks. Recall that, there are not any restrictions in APT theory about how long the markets would give a price to the factors. The priced factors may change from one period to another, and hence, using a quite large number of observations tends to shadow systematic effects that may had been significant for a short period of time. For example, if a factor was priced only during the financial crisis of 2007-2009 and one performs a t-statistic for a large period of time, this may shadow the systematic effects of this factor during the certain months of the crisis and come to a hasty conclusion that the factor was not priced at all. A counterexample though, is the case where one tests for premia within a short testing period and obtains spurious results due to temporary trends. Therefore, there is a trade-off between choosing to test for a short and a long period of time.

Furthermore, by performing separate t-statistics on the series of $\lambda_j's$ one is not testing the model. An F-statistic would give an estimation whether all these variables are statistically significant. There are many cases where t-statistics of certain variables appear to have explanatory power, but F-statistic is insignificant, indicating the entire model does not explain ex post returns. Moreover, by observing the adjusted R-squared we can estimate whether the inclusion of one variable improves the explanatory power of the model, regardless its significance appearing in the t-test. One more advantage when analyzing in a panel data form, is we can test whether there are random or fixed effects influencing the intercept. Both Fixed and Random effects models assume there is heterogeneity across the portfolios. The difference is that Fixed effects assume this heterogeneity is non-stochastic and thus they let each portfolio to have its own intercept, which comes in contrast to what we know from the APT theory about the same intercept cross-sectionally. If random effects model proves to be better than fixed effects, this may indicate that random effects influence the intercept of each portfolio and the stochastic component affects the residuals of the model. Rejecting both types of models, one can run a pooled regression which assumes homogeneity across the portfolio returns and thus, both slopes and intercept are assumed to be the same for every portfolio in the sample. This assumption fits perfectly with the APT, assuming we are estimating the true factors in the model.

Analyzing in a panel form of course has its disadvantages. One of these is the exposure of data to serial correlation and heteroskedasticity problems. Using the cross-sectional method, we would not have to worry about autocorrelation in the regressions, but the very fact that the procedure is followed by the separate t-statistics does not mean serial correlation problems do not exist. Using the panel alternative, we have to test for these problems and make analogous attempts to reduce their effects, such by using the generalized least squares method or requesting for corrected standard errors.

As equation (5.8) indicates, in the panel data analysis we have chosen to use annual returns to derive the annual premia, allowing beta coefficients change each calendar year. We also assume risk premiums remain time-invariant throughout the period we test in panel regression (testing period). We could just estimate monthly premia while using monthly portfolio returns and also let the factor loadings change each month, but in this case another problem arises which is related to the unit root process of the regressors (i.e. the series of factor loadings). In fact, we may implement such tests latter on to identify risk premiums within certain subperiods suggesting an alternative methodology, but we will show that this methodology seems not indicative (see subsection 6.5). Due to the nature of the APT multifactor model, it would be wrong to adjust the regressors (presumably by taking the first differences) in order to make the factor loadings stationary. All beta coefficients should enter the model without further adjustment. Letting the factor loadings change per annum we observed that all series were stationary[28]. An advantage of using annual returns instead of monthly portfolio returns is that our data are not exposed to seasonal effects such that of January effect and according to Antypas, Koundouri and Kourogenis (2013) annual returns tend to normality. What is more, we can see more clearly any relationship between the stock returns and the premia required by investors when undertaking certain risks as the cumulative returns of the following 12 months after the estimation period of factor loadings could represent more efficiently the unknown ex-ante required returns. Theoretically, the magnitude of factor loadings should not change regardless if we use monthly or annual returns, assuming these loadings do not change within each calendar year, as they reveal how much stock prices react to realizations of risky factors and are security-specific attributes. That is, if we increase (decrease) the time horizon of returns (frequency of observations), per annum, the time horizon of premia will increase but the factor loadings will not be affected due to their nature (they represent sensitivities) and the assumption we have imposed (their values change across years bur remain stable within each year). Notice that a specialized form of equation (5.8) where only a calendar year is tested, turns the panel form, to a cross-sectional regression and derives the annual premia for this year. Notice also, our suggested panel model does not restrict time observations to be greater than the cross-sectional observations, a restriction which is imposed in the non-linear model of Burmeister and McElroy (1988). In fact, the more we increase the cross-sectional observations (number of portfolios) the more reliable we expect our estimations will be, ceteris paribus.

To sum up, using panel data analysis we can estimate for priced factors over shorter periods of time while exploiting more observations than just running cross-sectionals. We can further test whether the model is appropriate which is better than simply estimating separately the parameters and finally, test for the presence of heterogeneity across the portfolios.

Notice that the dependent variable is in the form of excess portfolio returns. As we have presented in the derivation of the theory, the basic equation in APT imposes the intercept term to be the risk-free rate or if such a security does not exist, it is the rate of return of a portfolio which is not exposed to any kind of risk (zero-beta portfolio). Using excess returns on the left hand-side of the regression allows the risk-free rate to change month-by-month and we can further estimate whether the intercept of the regression (5.8) is statistically different from zero. Otherwise we would have to test whether the intercept equals the prevailing rate of the risk-free asset over the testing period.

[28] For each series of factor loadings, we run an Im-Pesaran-Shin unit root test. We regard this test to be appropriate as it allows for heterogeneity across the units (portfolios). We run every test with four lags allowing for a constant and trend. The overall test for every factor loading (considering all portfolios) revealed stationarity at the 1% level in all cases. In addition, when tested the factor loadings series for every portfolio separately, most portfolios' factor loadings series were stationary.

Regardless the procedure one follows in asset pricing models, heteroskedasticity and serial correlation problems will almost certainly arise. To deal with these problems we used the *Generalized Least Squares* method with *period weights* and *white period* robust estimators as we observed the errors within the cross-section units (i.e. portfolios) to be heteroskedastic and serially correlated when beta-sorted and MVE-sorted portfolios were tested. When tested the model with industry portfolios we used the *Generalized Least Squares* method with *cross-section weights* and *white diagonal* robust coefficient covariance estimators as heteroskedasticity problems were also revealed across-portfolios, presumably due to the fact that not all portfolios had achieved an adequate diversification allowing more errors with a non-constant variance. Before turning to this method though, several variations were used to ensure we obtain estimates consistent with theory.

The analytical procedure we followed to estimate for priced factors is described below:

i. We begin with our tests using the returns on portfolios formulated by securities' exposure to market risk as our dependent variable, since this method achieved a better spread on returns across the various portfolios.
ii. Following the steps 3 and 4 (described above) we obtained the series of betas of every portfolio on the specified factors.
iii. We then used a Random Effects model over the entire testing period to ensure there are no random variations. Based on Hausman's asymptotic test, p-value of the chi-square statistic was low enough, and hence a Random Effects model was not the appropriate one.
iv. In sequence, we run a Fixed Effects model and tested whether the groups have a common intercept. Since we use returns in excess of the risk-free rate, the intercept term does not represent the rate of return of the riskless asset, but its value indicates any omitted variables in our model. Ideally, if there was not any omitted variable in our model, we would expect to see an intercept of zero. P-value of the F-statistic was large enough and hence we could not reject the null hypothesis that the portfolio returns have a common intercept. Finally, we could proceed to a Pooled regression model.
v. Using a pooled regression model over the entire testing period, as well in subperiods we observed heteroskedasticity and autocorrelation problems and thus the errors within each portfolio had neither constant variance, nor were serially uncorrelated. When the errors are not homoscedastic, OLS estimators remain unbiased but are inefficient as the standard errors are often underestimated. Serial correlation also makes the R-squared and t-statistics to be overestimated in most cases, as heteroskedasticity does. To obtain robust standard errors we used the Generalized Least Squares method with period weights and accounted for a white period coefficient covariance method.

We started this procedure with the four basic variables proposed by Chen et al. (1986), that is unexpected industrial production growth, unanticipated inflation, unexpected changes of default premium and shifts in the slope of yield curve. We then added progressively the 2 remaining variables we suggested may serve as priced factors, that is policy uncertainty and developments in technology sector. To test whether our results are robust, we repeated all these tests using portfolios formulated by securities' firm 'size' and industry portfolios. Figure 5.5 depicts the procedure we followed to conclude to the Panel GLS models. In Table 5.7 we provide the Hausman test and the test for differing group intercepts for the three most appropriate models depending on the type of portfolios were tested (see Section 6). We do not present the results for all models tested, though results were similar.

Figure 5.5
The following chart-flow diagram presents the procedure implemented to identify the appropriate panel regression model.

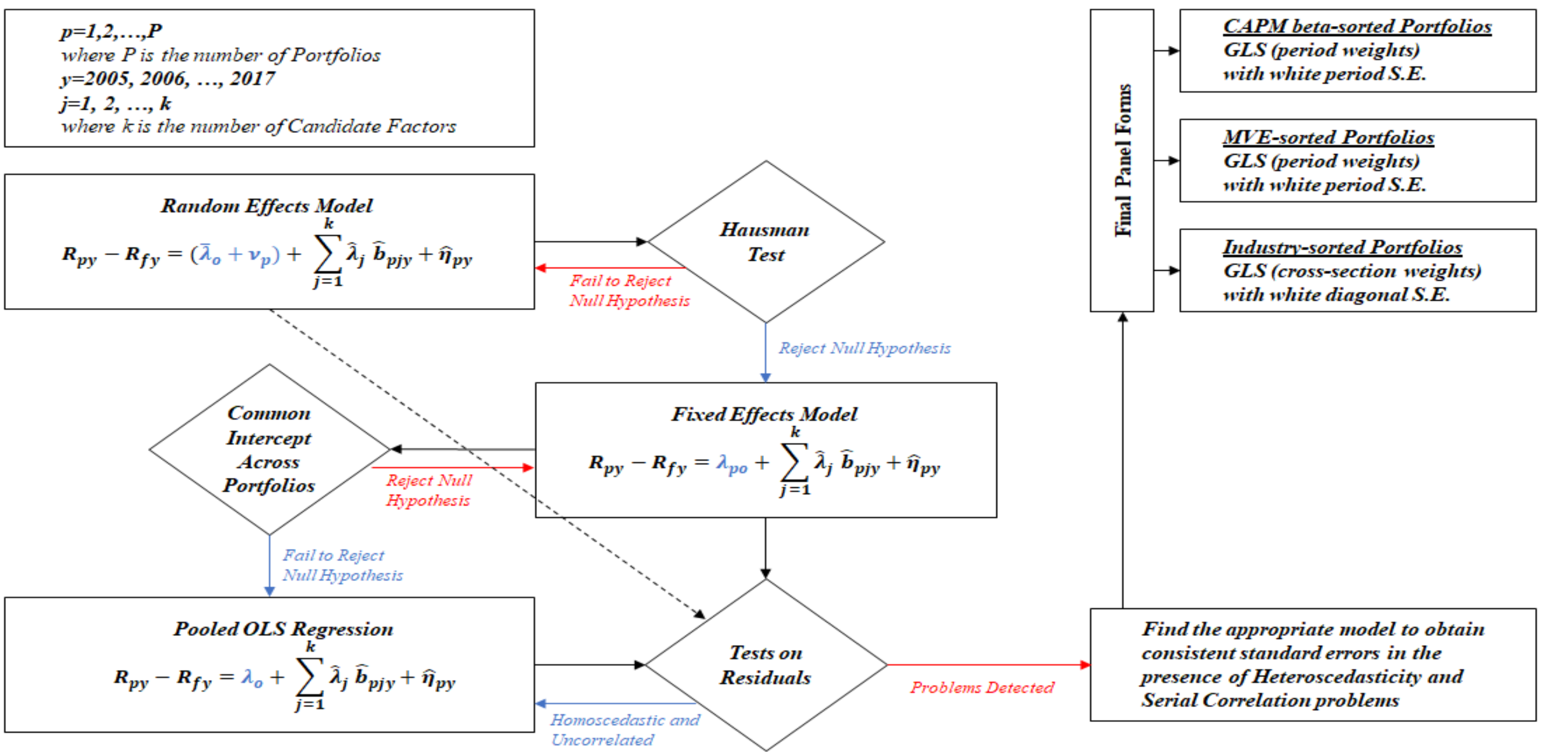


Table 5.7

The following table shows the results on two tests (the Hausman in Panel A and an F-test for differing group intercepts in Panel B) for three different regressions depending on the technique of portfolios formation (CAPM Beta-sorted, Market Capitalization sorted and Industry portfolios). For each of the three categories we have selected to present only the results of specific regressions (see "chosen model" below) as these regressions were estimated to give the "best" model in terms of factors selection (see section 6). Results however on all the other regressions (not presented here) are similar.

	Testing Assets (Portfolios)				
	Beta-sorted		**MVE-sorted**		**Industry-sorted**
Chosen model:	Panel F of Table 6.1		Panel E of Table 6.2		Panel E of Table 6.3
Panel A	**Hausman Test**				
Null Hypothesis:	*GLS estimates are consistent (use Random Effects model instead of Fixed)*				
Chi-square (5):	25.9866	**Chi-square (4):**	18.8441	**Chi-square (5):**	35.7725
P-Value:	8.98E-05	**P-Value:**	0.000843361	**P-Value:**	1.05E-06
Panel B	**Test for differing group intercepts**				
Null Hypothesis:	*Portfolios have a common intercept (use Pooled OLS instead of Fixed Effects model)*				
F (29,355):	0.956183	**F (29, 356):**	0.759912	**F (28, 343):**	1.41229
P-Value:	0.533914	**P-Value:**	0.812518	**P-Value:**	0.0838341

Section 6. «Results»

In the first part of this section we present our main findings when tested the pre-specified factors with portfolio returns arranged by the securities' simple CAPM betas. Thus, the 30 portfolios differ each other as they are exposed to systematic risks in different levels. We regard this technique will better explain the relationship between the risk factors and portfolio returns as we observed these portfolios achieved a better spread on their returns. In the second part we test the robustness of results using portfolios arranged by the securities market value of equity and in the third part we implement the same tests on industry portfolios. In subsection 6.4 we corroborate our findings by modifying realizations of two factors so as to be orthogonal to other factors where collinearity issues could potentially arise and finally in the last subsection, we let factor loadings to change per month and derive premiums within subperiods.

6.1 Market risk-sorted Portfolios

Table 6.1 represents the results of panel regressions using annual returns of 30 portfolios arranged by the securities' exposure to market risk as the dependent variable for the entire testing period of 13 years (from 2005 through 2017). To come up with autocorrelation and heteroskedasticity problems, we implemented the method of generalized least squares pooled regressions with period weights and used white period standard errors. We use adjusted R-squared to estimate whether the inclusion of a variable has improved the explanatory power of the model since it punishes for the degrees of freedom an extra variable adds in the model and thus estimate the within-the-sample predictability. Starting with Panel A, we regressed the four initial observable factors, suggested by Chen et al. (1986), namely unexpected growth of industrial production (UIP), unanticipated inflation (UINF), unanticipated changes of default premium (UDP) and shifts in the slope of yield curve (ΔTERM). As can be seen, all factors were significant at the 1% level except for the term-structure factor, which was not significant at all. Furthermore, inflation-related factor had a positive premium in contrast to the findings of Chen et al. (1986), an issue which will be discussed later on. In Panel B, we have excluded the insignificant value. Apparently, it would be wrong to simply run another regression of a reduced form as all these four variables were used in the regressions of the first-pass time series regressions to derive the beta coefficients (i.e. exposures of portfolios to each factor). This means that we have derived new beta estimates for all three variables by implementing again the first-pass methodology. Even if this procedure requires much more time is more reliable since, if a variable does not affect the pricing model, it should not influence all the remaining factors in the first-pass regressions. We may observe that the *ΔTERM* removal did not affect the premia of the remaining three factors but Adjusted R^2 fall by 3.18 percentage points. Up to this point, it seems that treasury's interest rates affect stock prices but are not priced by stock markets. This is the case where the beta coefficients of a factor appear significant in the first pass regressions but when these betas are regressed on future portfolio returns, risk premia are insignificant.

Table 6.1

This table reports the estimated annual risk premiums for the entire testing period (2005-2017) for different sets of factors when the testing assets were **30 portfolios arranged by the securities' exposure to market risk**. Premiums were estimated with a Panel Generalized Least Squares regression (period weights) with White Period Standard Errors to correct for autocorrelation and heteroskedasticity. Each panel consists of a total of 390 observations (30 portfolios; 13 years). For every Panel (A to G) a different set of factors were used in the two pass regressions (time-series regressions on factor realizations to estimate factor loadings; panel regressions on factor loadings to estimate premiums). Portfolio returns (dependent variable) were in excess of the risk-free rate. The factors are: unexpected growth of industrial production (*UIP*), unanticipated inflation (*UINF*), unexpected movements of default premium (*UDP*), shifts in the slope of the yield curve (*ΔTERM*), intensity of policy uncertainty (*UEPU*) and unexpected developments in technology sector (*UTG*). Numbers in bold denote estimated coefficients (i.e. risk premiums), numbers in parentheses are the standard deviations and numbers in square brackets are the t-statistics. Three stars (***) indicate significant values at the 1% level, two stars (**) at the 5% level and one star (*) at the 10% level respectively. The last three columns report the adjusted R-squared (Adj. R2), the Durbin Watson test for serial correlation on residuals (DW) and an F-statistic (F-stat) of which under the null hypothesis premiums for all factors (jointly) equal to zero.

Model:	Constant	UIP	UINF	UDP	ΔTERM	UEPU	UTG	Adj. R^2	DW	F-stat
Panel A										
	0.0095	**0.0254**	**0.0280**	**-0.0049**	**0.0009**			0.2472	1.93	32.94
	(0.0078)	(0.0041)	(0.0025)	(0.0012)	(0.0022)					
	[1.22]	[6.21]	[11.05]	[-4.21]	[0.40]					
		***	***	***						
Panel B										
	0.0216	**0.0275**	**0.0258**	**-0.0029**				0.2154	1.97	36.59
	(0.0077)	(0.0042)	(0.0021)	(0.0010)						
	[2.81]	[6.50]	[12.57]	[-2.86]						
	***	***	***	***						
Panel C										
	0.0402	**0.0246**	**0.0104**	**-0.0037**		**0.4940**		0.1721	2.16	21.22
	(0.0067)	(0.0040)	(0.0027)	(0.0008)		(0.0803)				
	[5.98]	[6.12]	[3.87]	[-4.74]		[6.15]				
	***	***	***	***		***				
Panel D										
	0.0304	**0.0236**	**0.0131**	**-0.0032**	**0.0015**	**0.2079**		0.1361	2.13	13.26
	(0.0063)	(0.0036)	(0.0028)	(0.0009)	(0.0019)	(0.0777)				
	[4.80]	[6.66]	[4.64]	[-3.70]	[0.76]	[2.68]				
	***	***	***	***		***				
Panel E										
	0.0197	**0.0223**	**0.0260**	**-0.0019**			**0.0114**	0.2706	1.87	37.09
	(0.0081)	(0.0045)	(0.0020)	(0.0009)			(0.0019)			
	[2.42]	[4.99]	[12.99]	[-2.29]			[6.14]			
	**	***	***	**			***			
Panel F										
	-0.0007	**0.0310**	**0.0223**	**-0.0064**	**-0.0156**		**0.0281**	0.3124	1.77	36.35
	(0.0087)	(0.0045)	(0.0026)	(0.0010)	(0.0040)		(0.0034)			
	[-0.09]	[6.87]	[8.69]	[-6.60]	[-3.93]		[8.33]			
		***	***	***	***		***			
Panel G										
	0.0150	**0.0235**	**0.0180**	**-0.0014**	**-0.0107**	**-0.3989**	**0.0245**	0.2131	1.81	18.56
	(0.0086)	(0.0044)	(0.0033)	(0.0012)	(0.0035)	(0.1106)	(0.0027)			
	[1.74]	[5.34]	[5.46]	[-1.14]	[-3.10]	[-3.61]	[9.09]			

	*	***	***		***	***	***

In Panel C we have included the policy-related factor (UEPU) on the three significant factors, which appears to have significant premia at the 1% level. In contrast to what we should expect from theory these premia are positive. Since this variable has its negative shocks to be a "good" indication for stock markets it should give a negative premium as well. Adjusted R^2 however has lowered its value to .1721 with the inclusion of this variable, indicating that its inclusion has weakened the model's explanatory power. The same result appears when *UEPU* was included in the regression with all four variables (see Panel D). Thus, we can estimate that *UEPU* does not really contain an extra information that the two spread factors do not capture and its inclusion gives spurious results.

In Panel E, we have regressed portfolio returns on the three initial significant factors along with unexpected developments in technology sector, *UTG*. Annual risk premia associated with *UTG* were positive and significant at the 1% level and comparing the results of Panel E with Panel B, premia associated with *UDP* were reduced and they turned significant at the 5% level. Adjusted R-squared though increased by 5.52%, indicating that the technology factor has improved the explanatory power of the model as its innovations contain superior information about stock prices fluctuations. In Panel F, the same factor has been added to all four initial factors. Comparing the results of Panel F with Panel A, *UTG* has enhanced the within-the-sample predictability and rendered the premia for ΔTERM significant at the 1% with a negative sign. Finally, in Panel G we have added again UEPU with the remaining 5 factors. UEPU had, consistent with theory, a negative premium and significant at the 1% but its inclusion made premia for UDP insignificant at any conventional level and further reduced the explanatory power of the model by almost 10 percentage points. Table 6.1 (as well tables 6.2 and 6.3) present(s) only the regressions we regard as more important to present our evidence. In fact, we implemented much more regressions of reduced forms to corroborate significant premiums were not spurious.

To sum up, using the CAPM beta-sorted portfolios to derive risk premia associated with pre-specified factors, we have shown that for the entire testing period from 2005 through 2017 a five-factor model could explain approximately one third of the variation of annual returns. Based on our sample, factors relevant to industrial production, inflation and developments in technology sector are significant sources of risk and bear a positive premium whilst two factors related to bond markets, namely, unanticipated changes of default spread and shifts in the slope of yield curve had a negative premium.

The interpretation of the positive premia for *UIP* and *UTG* is straightforward. Positive shocks related to industrial production and developments in technology sector are "good" news for stock prices and thus, investors require compensations for securities of which prices are positively correlated with these factors. Furthermore, stocks which react negatively to shocks on these factors will have a hedging value when the economy experiences poor performance. The positive premium for industrial production is consistent with the findings of Chen et al. (1986) and Chan et al. (1985) among others. In addition, the positive premium for risks inherent in aggregate technology agrees with the findings of Hsu (2009) and Hsu and Huang (2010).

Negative premia for UDP are also consistent with the corresponding factor "changes of risk premia" from the model of Chen et al. (1986). In fact, they found positive premia, but they derived the factor realizations as the difference between the returns of a portfolio of risky corporate bonds and the returns of a portfolio of long-term government bonds, so as positive shocks of this factor to represent "good" news for stock prices in general. In our methodology we have defined *UDP* as the shock occurred when the spread of Baa corporate yields over the Aaa corporate yields changes. In this case, positive shocks of *UDP* are "bad" news for stock prices, as it means that investors require much more compensations for the risky bonds, and thus should found a negative premium as we did. Put it another way, most stocks have a negative beta coefficient associated to realizations of *UDP*. The negative premia per unit of exposure multiplied by the negative exposure to default risk give a positive contribution to ex-ante returns. Therefore, investors require compensation for those stocks of which prices are negatively correlated to innovations of default spread. In our knowledge, all relevant studies have estimated consistent premia for this factor (i.e. see Chen et al. (1986), Chan et al. (1985), Ammer (1993)).

Derived premia associated with inflation and the term structure are more complicated to interpret though, as they are highly affected by the business cycles. In an inflationary environment, we would expect that positive shocks of inflation bring "bad" news for both investors and the issuing firms as it weakens the "strength" of all owners of capital and consumers afford to buy less quantities. Thereinafter, we would expect that those stocks of which prices rise with inflation to serve as a hedge against inflation and thus to find a negative premium consistent with the findings of Chen et al. (1986) and Chan et al. (1985). In the recent years however and especially after the financial crisis of 2008, the US economy does not suffer from high inflation at all. Thus, a positive shock of inflation is not necessarily "bad" news and an estimation a priori of the sign and the magnitude of the premia is not that easy. We attribute the positive premium for inflation risk as that investors would find "appealing" moderate positive inflation shocks as they would serve as an indication of a boost aggregate productivity.

In sequence, *ΔTERM*, the monthly changes of the spread between the 10-year and 3-month treasury yields should give premia, if any, of which magnitude and sign corresponds with the relevant economic conditions. Chen et al. (1986) and Chan et al. (1985) measured term structure as the difference between the returns of a portfolio of long-term government bonds minus the 3-Month T-Bill rate and found negative premia. They interpreted this result as stocks of which prices are inversely related to long-term rates are more valuable, but their sample consisted of a period where all rates were high enough. In March 1980 federal funds rate reached .20. Their equivalent premia, if measured with the spread of yields, as in our case, would be positive. Within the last two decades though, the US experienced low rates. According to the Federal Reserve Bank of St. Louis, for our sample period (from 2000 through 2017) the 3-Month Treasury (Constant maturity) rate has reached a peak of 6.38% in October 2000, followed by a decline until the late 2003. Then the rates increased reaching 5.16% in February 2007 and again experienced a sharp decline with these rates being almost zero from the late 2008 through the late 2015. The federal funds rate also draw their lowest value of .25% in December 2008. The 10-Year treasury (Constant maturity) had its highest rate of 6.68% in January 2000 (first month in our sample) and up to 2017 it fluctuates with a declining trend. The first 5 years of our data have been used to derive the first values of the series of beta coefficients and our testing period consists of all years between 2005 and 2017. From 2009, where the short-term rates are almost zero, *ΔTERM* is mostly affected by the long-term rates, and thus it's the fluctuations of the 10-year rates that influences mostly the pricing result of *ΔTERM* in our model. The higher the long-term rates, the more expensive the financial support to companies. In this point of view, we would expect that the willingness of firms to undertake projects is moderated when long rates increase due to higher costs. Thus, a negative premium for *ΔTERM* seems meaningful. Investors find appealing those companies of which profits increase when the long-term rates increase. Another interpretation is that, given the short-rates constant, a positive shock of *ΔTERM* has been caused due to the higher yields investors require to lend money to the Government. Given the fact that yields move inversely to bond prices, investors will attain higher yields as they will buy those bonds in lower prices and the negative *ΔTERM* premium indicates that stocks of which prices increase when bond prices decline are more valuable. In our sample period, it seems that bondholders in general could hedge for this risk by investing in stock markets. In a counterexample though, according to expectations hypothesis when the slope of the yield curve is steep investors draw positive prospects about the economy, meaning that a positive shock of *ΔTERM* brings "good" news and we would expect to see a positive premium for this risk. Furthermore, in an inflationary environment we could expect short-term rates to increase as a tool to come up with inflation and a flattening yield curve would bring "bad" news to investors. Since the short-term rates are almost zero within a large subperiod of the sample, a marginal change in the shape of the yield curve due to changes in the rate of long-term bonds would not necessarily have the same effects. Consistent with our results, Ammer (1993) has also found a negative premium for the term-factor in most of the periods tested. Therefore, it would not surprise as to observe both positive and negative signs on different subperiods. An analysis of these premia into short subperiods anyway will be more confusing as we may have to take into consideration all these aspects behind the structure of interest rates.

The policy-related factor, if priced, should bring a negative premium as a positive shock of *UEPU* brings "bad" news to investors. This is equal to saying that stocks of which prices rise in periods of high policy uncertainty should be more valuable. The fact that we found no pricing effect is an indication that *UDP* and *ΔTERM* capture uncertainty and *UEPU* has no additional explanatory power. But it remains to corroborate these findings when different portfolio formations are implemented. Moreover, it would not surprise us to find significant negative premia for UEPU within the months of economic crisis in 2008.

6.2 MVE-sorted Portfolios

Implementing the methodology with portfolios arranged by the securities' firm size, table 6.2 presents annual risk premia associated with the observable factors for the entire testing period from 2005 through 2017. Starting again with the four initial factors (see Panel A) we found positive premia for *UIP*, *UINF* and *ΔTERM* and a negative premium for *UDP*, all significant at the 1% level. Notice this time, *ΔTERM* has a positive premium. Adding *UEPU* as an additional factor (see Panel B), *UDP* and *ΔTERM* turned insignificant, same as *UEPU* and adjusted R-squared fall almost 12 percentage points. In Panel C we have added UTG as an additional factor in the model of four initial factors and found a positive and statistically significant premium at the 1% level, but its inclusion made the premia for *UDP* and *ΔTERM* insignificant though adjusted R-squared increased from .25 to .34.

Table 6.2

This table reports the estimated annual risk premiums for the entire testing period (2005-2017) for different sets of factors when the testing assets were **30 portfolios arranged by the securities' market value of equity**. Premiums were estimated with a Panel Generalized Least Squares regression (period weights) with White Period Standard Errors to correct for autocorrelation and heteroskedasticity. Each panel consists of a total of 390 observations (30 portfolios; 13 years). For every Panel (A to E) a different set of factors were used in the two pass regressions (time-series regressions on factor realizations to estimate factor loadings; panel regressions on factor loadings to estimate premiums). Portfolio returns (dependent variable) were in excess of the risk-free rate. The factors are: unexpected growth of industrial production (*UIP*), unanticipated inflation (*UINF*), unexpected movements of default premium (*UDP*), shifts in the slope of the yield curve (*ΔTERM*), intensity of policy uncertainty (*UEPU*) and unexpected developments in technology sector (*UTG*). Numbers in bold denote estimated coefficients (i.e. risk premiums), numbers in parentheses are the standard deviations and numbers in square brackets are the t-statistics. Three stars (***) indicate significant values at the 1% level, two stars (**) at the 5% level and one star (*) at the 10% level respectively. The last three columns report the adjusted R-squared (Adj. R2), the Durbin Watson test for serial correlation on residuals (DW) and an F-statistic (F-stat) of which under the null hypothesis premiums for all factors (jointly) equal to zero.

Model:	Constant	UIP	UINF	UDP	ΔTERM	UEPU	UTG	Adj. R^2	DW	F-stat
Panel A										
	-0.0174	**0.0291**	**0.0310**	**-0.0067**	**0.0067**			0.2514	2.16	33.66
	(0.0127)	(0.0036)	(0.0026)	(0.0019)	(0.0021)					
	[-1.37]	[8.08]	[11.84]	[-3.61]	[3.17]					
		***	***	***	***					
Panel B										
	0.0335	**0.0297**	**0.0185**	**0.0003**	**0.0029**	**0.1377**		0.1367	2.21	13.32
	(0.0131)	(0.0038)	(0.0027)	(0.0020)	(0.0023)	(0.0997)				
	[2.56]	[7.86]	[6.98]	[0.13]	[1.29]	[1.38]				
	**	***	***							
Panel C										
	-0.0065	**0.0376**	**0.0340**	**-0.0032**	**-0.0030**		**0.0186**	0.3405	2.06	41.17
	(0.0160)	(0.0045)	(0.0023)	(0.0022)	(0.0032)		(0.0027)			
	[-0.41]	[8.30]	[15.05]	[-1.42]	[-0.94]		[6.78]			
		***	***				***			
Panel D										
	0.0103	**0.0416**	**0.0345**	**0.0008**			**0.0160**	0.3354	2.10	50.09
	(0.0156)	(0.0044)	(0.0019)	(0.0024)			(0.0016)			
	[0.66]	[9.45]	[18.55]	[0.32]			[10.02]			
		***	***				***			
Panel E										
	0.0096	**0.0215**	**0.0206**		**-0.0034**		**0.0141**	0.3670	2.04	57.38
	(0.0075)	(0.0029)	(0.0021)		(0.0017)		(0.0023)			
	[1.28]	[7.35]	[9.96]		[-2.03]		[6.22]			
		***	***		**		***			

In Panel D we removed *ΔTERM* and adjusted R-squared fall by a half percent. *UDP* were again insignificant. In Panel E we have added again *ΔTERM* and removed *UDP*. Adjusted R-squared ascended to 36.7% and all variables were significant at the 1% level. Consistent with our findings when market beta-sorted portfolios were tested, *UIP*, *UINF* and *UTG* had a positive annual premium whilst *ΔTERM* a negative one, but *UDP* seems not a priced factor using this alternative method. Even though these findings are quite encouraging, especially for *UINF* and *ΔTERM* where its premia are quite sensitive to the period tested, we have reasons to believe that our first alternative method (see subsection 6.1) has given more reliable results since portfolios achieved a better spread on their returns.

Again, more regressions were run than those presented in table 6.2 to corroborate our findings. We have chosen to present those 5 regressions (Panels A to E) that we regard as of high importance to present our findings. It remains to corroborate our findings with our third alternative method.

6.3 Industry Portfolios

Table 6.3 presents the estimated annual risk premia associated with observable factors using industry portfolios. We have required a portfolio to contain at least 10 securities to include it in our tests, so 29 industry portfolios have been formed and not all securities in our sample have been tested. Since there are many portfolios with only a few securities we should suspect that significant idiosyncratic errors have distorted both the estimated premia and the forecastability of the model. For these series of tests, we implemented the Generalized Least Squares panel regression method with cross-section weights and white diagonal standard errors as we have found heteroskedasticity problems both within the portfolios as well as across portfolios. Presumably, heteroskedasticity across the portfolios is related to the heterogeneity across industries. During the financial crisis, most stocks also became more volatile and thus we would expect heteroskedasticity within the portfolios to be a reasonable outcome. The latter, was also observed on portfolio formations related to subsections 6.1 and 6.2.

Similar with our findings using the first method of portfolios formation, when regressed industry portfolio returns on their factor loadings on *UIP*, *UINF*, *UDP* and *ΔTERM* (see Panel A) we found a negative premium for *UDP* which was significant at the 1% level and positive premia for *UIP* and *UINF*, significant at the 5% and 1% level respectively. *ΔTERM* was not significant at any conventional level but when we removed this factor from the model (both at the first and second pass regressions) adjusted R-squared fall by 1.63% and moderated the significance of *UDP*, at 10% (see Panel B). In Panel C we have added *UEPU* on the initial four factors which reduced the explanatory power of the model and was not significant at all. Without *ΔTERM, UEPU* again did not improve the within-the-sample forecastability (see Panel D). On the contrary, *UTG* has improved the explanatory power of the pricing model. The best model, in terms of within-the-sample forecastability for the entire testing period seems to be the five-factor model of Panel E. The major difference between the five-factor model of this alternative portfolio formation method and the corresponding model of the beta-sorted portfolio formation is that *ΔTERM* is now significant at the 5% level instead of 1% level. Furthermore, in contrast to the second alternative methodology, this alternative has corroborated the pricing effect of *UDP*.

Table 6.3

This table reports the estimated annual risk premiums for the entire testing period (2005-2017) for different sets of factors when the testing assets were **29 industry portfolios**. Premiums were estimated with a Panel Generalized Least Squares regression (cross-section weights) with White Diagonal Standard Errors to correct for autocorrelation and heteroskedasticity. Each panel consists of a total of 377 observations (29 portfolios; 13 years). For every Panel (A to F) a different set of factors were used in the two pass regressions (time-series regressions on factor realizations to estimate factor loadings; panel regressions on factor loadings to estimate premiums). Portfolio returns (dependent variable) were in excess of the risk-free rate. The factors are: unexpected growth of industrial production (*UIP*), unanticipated inflation (*UINF*), unexpected movements of default premium (*UDP*), shifts in the slope of the yield curve (*ΔTERM*), intensity of policy uncertainty (*UEPU*) and unexpected developments in technology sector (*UTG*). Numbers in bold denote estimated coefficients (i.e. risk premiums), numbers in parentheses are the standard deviations and numbers in square brackets are the t-statistics. Three stars (***) indicate significant values at the 1% level, two stars (**) at the 5% level and one star (*) at the 10% level respectively. The last three columns report the adjusted R-squared (Adj. R2), the Durbin Watson test for serial correlation on residuals (DW) and an F-statistic (F-stat) of which under the null hypothesis premiums for all factors (jointly) equal to zero.

Model:	Constant	UIP	UINF	UDP	ΔTERM	UEPU	UTG	Adj. R^2	DW	F-stat
Panel A										
	-0.0074	**0.0167**	**0.0209**	**-0.0081**	**0.0022**			0.1228	2.08	14.16
	(0.0210)	(0.0066)	(0.0035)	(0.0025)	(0.0025)					
	[-0.35]	[2.54]	[6.01]	[-3.21]	[0.88]					
		**	***	***						
Panel B										
	0.0101	**0.0171**	**0.0212**	**-0.0050**				0.1065	2.08	15.93
	(0.0210)	(0.0069)	(0.0033)	(0.0026)						
	[0.48]	[2.46]	[6.46]	[-1.91]						
		**	***	*						
Panel C										
	0.0236	**0.0152**	**0.0156**	**-0.0044**	**0.0023**	**0.2415**		0.0601	2.15	5.81
	(0.0209)	(0.0066)	(0.0038)	(0.0028)	(0.0026)	(0.1858)				
	[1.13]	[2.31]	[4.11]	[-1.56]	[0.86]	[1.30]				
		**	***							
Panel D										
	0.0524	**0.0117**	**0.0162**	**-0.0014**		**0.4511**		0.0612	2.17	7.13
	(0.0207)	(0.0073)	(0.0036)	(0.0028)		(0.1925)				
	[2.53]	[1.60]	[4.50]	[-0.48]		[2.34]				
	**		***			**				
Panel E										
	-0.0266	**0.0270**	**0.0172**	**-0.0088**	**-0.0065**		**0.0193**	0.1739	2.07	16.83
	(0.0223)	(0.0064)	(0.0033)	(0.0025)	(0.0030)		(0.0031)			
	[-1.20]	[4.24]	[5.27]	[-3.56]	[-2.19]		[6.33]			
		***	***	***	**		***			
Panel F										
	-0.0003	**0.0260**	**0.0196**	**-0.0039**			**0.0112**	0.1376	2.11	16.00
	(0.0226)	(0.0069)	(0.0032)	(0.0026)			(0.0023)			
	[-0.01]	[3.75]	[6.17]	[-1.52]			[4.86]			
		***	***				***			

So far, we have found that five observable factors are significant sources of risk in the US stock markets for the period from 2005 through 2017. According to the first technique of portfolios formation based on securities' exposure to market risk, the five-factor model could explain approximately one third of the variation of annual portfolio returns for the entire testing period. Though not exactly the same, the results were not in conflict when market capitalization-sorted or industry-sorted portfolios were used on tests. The latter observation is quite encouraging and calls for further investigations as it may be the case where our proposed methodology is better than the conventional methodology. Clare and Thomas (1994) had found that beta-sorted portfolios revealed different premiums than firm size-sorted portfolios did and derived a quite different macroeconomic model depending on the criterion of portfolios formation. We presume our methodology discloses better the relationship between returns and risks as we have used annual returns on the second-pass series tests. Testing for monthly compensations we would expect that seasonal effects could shadow the pricing results.

6.4 A Variant Technique to Derive Factor Realizations

In this subsection we use a variant technique to derive the realizations of the two additional factors proposed in our model, namely *UEPU* and *UTG*. Instead of using the residuals of parsimonious ARMA models as a proxy for their innovations we restrict their shocks to be orthogonal to shocks occurred by other correlated variables. Even if we do not face severe multicollinearity problems, we want to make sure that innovations associated with policy-related economic uncertainty and developments in technology sector are independent of the remaining factor realizations to corroborate our previous findings. To derive innovations for policy uncertainty we run the following OLS regression:

$$\boldsymbol{EPUG_t = \hat{a}_0 + \sum_{i=1}^{4} \hat{a}_i\, EPUG_{t-i} + \hat{a}_5\, EPUG_{t-7} + \hat{a}_6\, UDP_t + \hat{a}_7\, \Delta TERM_t + \hat{\theta}_{EPU,t}} \qquad (6.4.1)$$

where, $\boldsymbol{\hat{\theta}_{EPU}}$ are the residuals or better, the derived shocks which will be used in the first-pass time series regressions to derive the beta coefficients of portfolio returns on policy uncertainty factor. Series for *EPUG*, *UDP* and *ΔTERM* have been presented in Section 5. We have not included lags of the fifth and sixth order of the monthly *EPUG* series since they were not statistically significant. Using this regression to derive the shocks we have restricted shocks associated with policy uncertainty to be uncorrelated with unanticipated changes of default premium and shifts in the slope of the yield curve as the latter two variables are affected by economic uncertainty. One could argue this technique is more reliable as we can test whether policy uncertainty contains an extra pricing information that the two bond-spread factors do not capture, though we impose restrictions on the estimated shocks of policy uncertainty. Similar, for unexpected growth of technology sector we used the residuals of the following regression:

$$\boldsymbol{TG_t = \hat{c}_0 + \sum_{i=1}^{6} \hat{c}_i \, TG_{t-i} + \hat{c}_7 \, UIP_t + \hat{c}_8 \, UINF_t + \hat{c}_9 \, \Delta TERM_t + \hat{c}_{10} \, UDP_t + \hat{\eta}_{TG,t}} \qquad (6.4.2)$$

where, $\boldsymbol{\hat{h}_{TG}}$ are the estimated shocks (i.e. unexpected components) of technology growth and will be used in the first-pass time series regressions to derive the corresponding factor loadings of portfolio returns on technology growth. Series for *TG, UIP, UINF, ΔTERM* and *UDP* have been presented in Section 5. Following the above technique, we have restricted technology factor to generate shocks that do not coincide with shocks on industrial production, inflation and the two factors derived by the bond markets. To avoid any ambiguity, the two techniques implemented in equations (6.4.1) and (6.4.2) do not represent any causal effect. For instance, a positive shock on industrial production could have been generated by an innovation on technology sector but in this case $\boldsymbol{\hat{h}_{TG}}$ will not have captured this effect. With this rigorous restriction we seek to assess whether indices associated with policy uncertainty and technology really hide an extra information, useful in asset pricing models, at least for the period we test. As we have already discussed in Sections 4 and 5, factor realizations should be mean zero, serially uncorrelated and should not expose correlations with the other factors. All these conditions hold for the two series and are presented in Appendix C.

Table 6.4 presents the premia when the CAPM beta-sorted portfolios were tested. The only difference with table 6.1 is the technique used to derive innovations for the last two variables as presented in equations (6.4.1) and (6.4.2). The first two Panels are exactly the same as in table 6.1 as we have not imposed restrictions on shocks associated with *UIP*, *UINF*, *UDP* and *ΔTERM*. In Panel C we have added the restricted shocks of policy related factor, which is not priced at any conventional level and has (again) reduced the explanatory power of the model. Adjusted R-squared fall almost 10 percentage points. Based on our sample, we cannot reject the null hypothesis that policy-related uncertainty contains no extra pricing information that the two bond-related factors cannot capture, at least for the entire testing period. In Panel D we have added the restricted shocks of technology-related factor on the initial four-factor model. The factor is positively priced at the 1% level and enhanced the estimated premium for *ΔTERM*, which is now negatively priced at the 1% level. Furthermore, its inclusion enhanced the within-the-sample forecasting ability of the model as adjusted R-squared has increased by almost 7%. Notice these results match with the corresponding premia derived with no restrictions (see Panel F of table 6.1).

We expect that if policy uncertainty factor was not significant in the regressions of table 6.1 due to multicollinearity problems but was a significant parameter in the true (unknown) pricing model, then table 6.4 should reveal a statistically significant premium for this factor. Furthermore, in table 6.1 technology factor could give spurious premia in case where shocks occurred in technology sector were coincident with shocks of different source. For instance, inflation could affect technology nominal growth and shocks observed on such an index would not really be technology innovations. In this case, we would expect technology-related premium in table 6.4 to be insignificant as we have restricted those shocks to be orthogonal to shocks of the first four factors. Its significance lends further support to the alternative hypothesis that technology growth is a systematic source of risk on stock prices, at least when annual premia have been tested for the entire testing period.

Table 6.4

This table reports the estimated annual risk premiums for the entire testing period (2005-2017) for different sets of factors when the testing assets were **30 portfolios arranged by the securities' exposure to market risk**. Premiums were estimated with a Panel Generalized Least Squares regression (period weights) with White Period Standard Errors to correct for autocorrelation and heteroskedasticity. Each panel consists of a total of 390 observations (30 portfolios; 13 years). Results on Panels A and B are exactly the same as in Panels A and B of table 6.1 as factor realizations for UIP, UINF, UDP and ΔTERM have not imposed a restriction. Results on Panels C and D differ from the corresponding results of Panels D and F of table 6.1 as factor realizations for policy-related uncertainty (ϑ_{EPU}) and technology developments (η_{TG}) have imposed restrictions (see equations 6.4.1 and 6.4.2). Portfolio returns (dependent variable) were in excess of the risk-free rate. Numbers in bold denote estimated coefficients (i.e. risk premiums), numbers in parentheses are the standard deviations and numbers in square brackets are the t-statistics. Three stars (***) indicate significant values at the 1% level, two stars (**) at the 5% level and one star (*) at the 10% level respectively. The last three columns report the adjusted R-squared (Adj. R2), the Durbin Watson test for serial correlation on residuals (DW) and an F-statistic (F-stat) of which under the null hypothesis premiums for all factors (jointly) equal to zero.

Model:	**Constant**	**UIP**	**UINF**	**UDP**	**ΔTERM**	ϑ_{EPU}	η_{TG}	**Adj. R^2**	**DW**	**F-stat**
Panel A										
	0.0095	**0.0254**	**0.0280**	**-0.0049**	**0.0009**			0.2472	1.93	32.94
	(0.0078)	(0.0041)	(0.0025)	(0.0012)	(0.0022)					
	[1.22]	[6.21]	[11.05]	[-4.21]	[0.40]					
		***	***	***						
Panel B										
	0.0216	**0.0275**	**0.0258**	**-0.0029**				0.2154	1.97	36.59
	(0.0077)	(0.0042)	(0.0021)	(0.0010)						
	[2.81]	[6.50]	[12.57]	[-2.86]						
	***	***	***	***						
Panel C										
	0.0254	**0.0253**	**0.0152**	**-0.0023**	**0.0027**	**0.1333**		0.1470	2.10	14.41
	(0.0068)	(0.0038)	(0.0029)	(0.0008)	(0.0020)	(0.0900)				
	[3.72]	[6.73]	[5.30]	[-2.81]	[1.40]	[1.48]				
	***	***	***	***						
Panel D										
	-0.0001	**0.0258**	**0.0247**	**-0.0061**	**-0.0124**		**0.0210**	0.3162	1.79	36.97
	(0.0080)	(0.0046)	(0.0025)	(0.0009)	(0.0038)		(0.0028)			
	[-0.01]	[5.63]	[10.01]	[-6.86]	[-3.25]		[7.39]			
		***	***	***	***		***			

6.5 Allowing Factor Loadings to Vary Month-by-Month

In most of the cases in the conventional literature an assumption of stable betas per month was imposed within each calendar year. Authors used to run 12 monthly cross-sectional regressions of portfolio returns on the same risk exposures (for instance see the work of Chen et al. (1986), Chan et al. (1985) and Clare and Thomas (1994)). These beta estimates would vary across years but remain stable within each annum. In our knowledge, only Hamao (1988) attempted to derive risk premia allowing exposures to macroeconomic variables change each month and thus, every monthly cross-sectional regression had unique beta values. In this subsection we implement further tests allowing all factor loadings to change each month. The model we proposed in our main methodology was already a conditional model in terms that betas could vary across time. The question however is, what if we change the frequency of this variation? Do our results still seem robust on alternate portfolio formations? Or even, could we obtain reliable estimates within short subperiods given the fact that exposure profiles vary depending on certain months (i.e. during the financial crisis)? To answer, we change our methodology as:

Step 1: For the period from January 2000 through December 2004 (60 monthly observations) we run an OLS time series regression for every portfolio separately where the dependent variable is the monthly portfolio excess returns and the regressors are the realizations of observable factors to derive each portfolio’s factor loadings (betas). These betas will further be used in the panel analysis to explain, along with a constant parameter, the portfolio excess returns of the first month following these 60 months of the estimation period, that is January 2005.

Step 2: We then roll forward the period of 60 observations by one month, that is from February 2000 through January 2005 and further estimate new betas for each portfolio on every factor. These new beta estimates will further be used in the panel analysis to explain the portfolio excess returns of February 2005.

Step 3: We repeat the process of step 2 until we derive a series of monthly observations of beta estimates for every portfolio on each factor from January 2005 through December 2017 and implement a panel data analysis where the dependent variables are the monthly excess returns of every portfolio from January 2005 through December 2017 and the regressors are the series of these beta estimates.

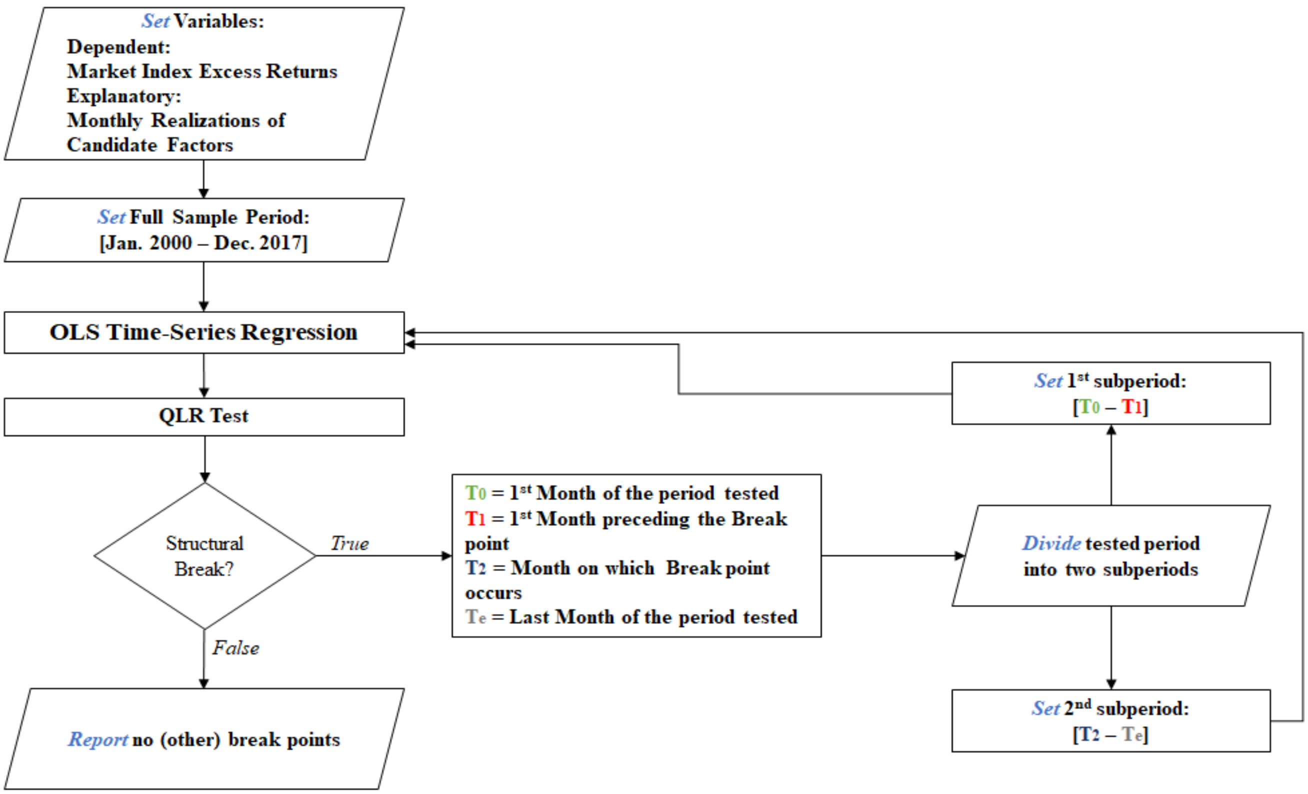
With this procedure we allow beta coefficients to change every month throughout the testing period. In contrast to our main methodology, coefficients of this alternative represent the estimated *per month* premiums but again these premiums are assumed to remain stable during the period we test. In an attempt to identify structural breaks, we regressed S&P500 excess returns on the factor realizations for the entire sample period and performed a QLR test[29] which identifies endogenously any break point. We present the procedure of structural break identification in Figure 6.1. Whenever we identify a break, we split the sample into subsamples to test for further break points. Overall, we found two structural breaks, one occurred on March 2010 and another on April 2013.

[29] Quandt Likelihood Ratio test performs Chow tests at frequent points within the period of question and identifies the maximum F statistic and further tests if at this point a structural break occurs.

QLR results are shown in figure 6.2. Though we cannot be sure whether these dates are really important to regard them as breaks due to the complexity of the two-pass regressions we run in these methodologies and due to the fact that we found these breaks on the market index instead of the portfolios, we presume is a good approximation to split the sample into subsamples and further test whether the effectiveness of the factors change conditional to these structural breaks. Notice also that the tests did not identify a structural break during the financial crisis of 2007-2009 but we may further see the effects of the crisis in a second series of tests.

Figure 6.1

The following chart-flow diagram depicts the procedure followed to identify potential structural breaks.



The methodology we implemented in the second-pass (panel form) tests is *time-fixed effects* as we observed highly significant time effects and used *white period* coefficient covariance standard errors due to heteroskedasticity within the portfolios. We run these tests with CAPM beta-sorted portfolios, following the same arguments as in our main methodology. In contrast with our main findings when derived annual premia for the factors, we observed that the methodology behind the portfolio formation really matters as the results are disturbingly different, but we present only regressions on the CAPM beta-sorted portfolios as they have achieved a better spread on returns and seem to have an adequate diversification. Nevertheless, the very fact that results are now quite sensitive on testing assets should be considered as a notable drawback and this (alternative) methodology should be assessed with caveats. It is important to mention that by using time-fixed effects panel regressions we were not exposed to serial correlation problems at least for a small number of lags, an issue that we now observed when time-fixed effects model was substituted by the Generalized Least Squares method. With these pooled OLS regressions, we retain the assumption that idiosyncratic returns are not serially correlated. In a time-fixed effects model, we assume constant slopes across the portfolios but the constant parameter changes through time. If we were testing portfolio returns without subtracting the equivalent risk-free rate and the observable factors were the true (unknown) factors, we would expect time-effects to capture the risk-free rate. Since, we use portfolio excess returns we presume these effects were significant as they corrected for omitted variables.

We used several two-pass series tests repetitions with a different set of factors for each subperiod before we found the model that "best" forecasts portfolio returns. For each subperiod we found a different set of risks that are priced in the market. In table 6.5 we present the "best" models we could derive. As we have already described, when a factor has insignificant premia should not only dropped out from the panel model but the estimation of the factor loadings in the first-pass time series regressions should be implemented again without regarding this variable. We were indulgent in one case though. When a factor was not priced at all but its inclusion had helped the remaining variables to have more reliable coefficients, we made an exception and retained this variable in our model as an effort to mitigate errors in the loadings of the remaining factors. This "paradox" would not be observed in an APT model with the true parameters. APT is strict in terms that the priced factors which enter the *return generating process* are the same factors of which loadings help forecast returns through the *basic APT equation*. We could resemble these unpriced factors that increase adjusted R-squared as control variables.

Figure 6.2

The following two diagrams are related to the two structural breaks found via QLR tests.

Final Reports on QLR tests	
1st **Structural Break** observed on **March 2010** Where the maximum F(7,202)=3.7655. Chi-square(7) = 26.3585. Asymptotic P-value = 0.01038.	2nd **Structural Break** observed on **April 2013** Where the maximum F(7,80)=3.3672. Chi-square(7) = 23.5702. Asymptotic P-value = 0.02787.

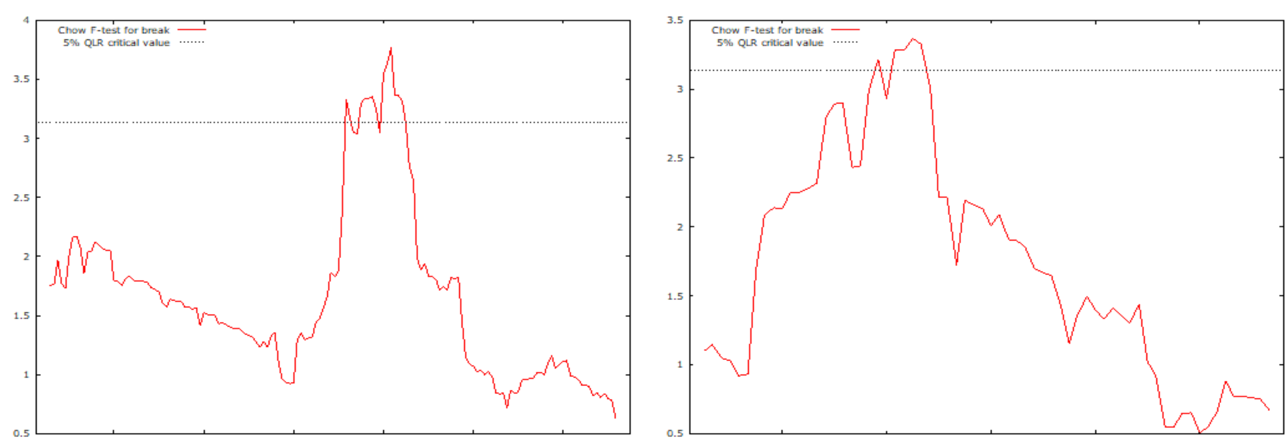


Table 6.5

This table reports the estimated monthly risk premiums for the entire testing period as well for three subperiods defined by two structural breaks (03/2010 and 04/2013). For all panel regressions we used time-fixed effects models with white period S.E and the dependent variables were monthly excess returns of **30 portfolios arranged by the securities' exposure to market risk**. Regressors are factor loadings of which values change per month. Each Panel (A to D) reports the derived premiums for different testing periods. In every Panel only the results on the "best model" (in terms of within-the-sample forecastability) are shown. That means, for every testing period, starting with a set of six factors (UIP, UINF, UDP, ΔTERM, UEPU and UTG) we removed progressively one-by-one factors of which (1) their relevant premiums were statistically insignificant and (2) their inclusion could not increase Adjusted R-squared. *UEPU* does not appear in this table as was not significant in every testing period. We define the "best model" as the one consisting of factors which improve Adj. R^2. Whenever *UTG* appears significant, another regression was run where *UTG* was substituted by $\boldsymbol{\eta}_{TG}$ (restricted shocks on tech-factor, see equation 6.4.2) to corroborate its significance. Numbers in bold denote estimated coefficients (i.e. risk premiums), numbers in parentheses are the standard deviations and numbers in square brackets are the t-statistics. Three stars (***) indicate significant values at the 1% level, two stars (**) at the 5% level and one star (*) at the 10% level respectively. The last three columns report the adjusted R-squared, the Durbin Watson (DW) test for serial correlation on residuals and the Wald-statistic of which under the null hypothesis premiums for all factors (jointly) equal to zero. In Wald tests we have not included the time effects.

Constant	**UIP**	**UINF**	**UDP**	**ΔTERM**	**UTG**	$\boldsymbol{\eta}_{TG}$	**Adj. R^2**	**DW**	**Wald**
Panel A		Entire Testing Period:		[01/2005 - 12/2017]			Panel Observations:		4,680
-0.00051	**0.00385**		**-0.00025**	**-0.00030**			0.7470	2.14	121.24
(0.00059)	(0.00056)		(0.00005)	(0.00014)					
[-0.87]	[6.83]		[-4.77]	[-2.12]					
	***		***	**					
Panel B		1st Subperiod:		[01/2005 - 02/2010]			Panel Observations:		1,890
-0.00916	**0.00532**	**0.00135**	**-0.00048**		**0.00074**		0.7877	2.04	46.02
(0.00112)	(0.00106)	(0.00051)	(0.00012)		(0.00036)				
[-8.18]	[5.04]	[2.67]	[-3.99]		[2.05]				
***	***	***	***		**				
-0.00889	**0.00518**	**0.00138**	**-0.00042**			**0.00050**	0.7876	2.04	45.14
(0.00109)	(0.00104)	(0.00052)	(0.00011)			(0.00032)			
[-8.19]	[4.97]	[2.65]	[-3.63]			[1.58]			
***	***	***	***						
Panel C		2nd Subperiod:		[03/2010 - 03/2013]			Panel Observations:		1,110
0.00682	**-0.00051**	**-0.00038**	**0.00002**	**0.00155**	**0.00086**		0.7468	2.23	61.4
(0.00121)	(0.00085)	(0.00055)	(0.00023)	(0.00053)	(0.00031)				
[5.62]	[-0.60]	[-0.68]	[0.10]	[2.91]	[2.73]				
***				***	***				
0.00621	**-0.00037**	**-0.00031**	**0.00001**	**0.00157**		**0.00097**	0.7467	2.23	63.65
(0.00118)	(0.00081)	(0.00057)	(0.00022)	(0.00053)		(0.00029)			
[5.25]	[-0.45]	[-0.55]	[0.07]	[2.95]		[3.35]			
***				***		***			
Panel D		3rd Subperiod:		[04/2013 - 12/2017]			Panel Observations:		1,170
0.00681	**0.00349**			**-0.00019**			0.6187	2.27	33.02
(0.00086)	(0.00066)			(0.00014)					
[7.90]	[5.32]			[-1.39]					
***	***								

Based on the results shown in table 6.5 for the entire testing period, that is all months from January 2005 through December 2017 (see Panel A) we only found three risk premia which were inherent with the systematic observable factors. One of these premia was positive and statistically significant at the 1% level, that is monthly premium related to industrial production growth. The remaining two bond market related factors had a negative premium. Default premium was significant at the 1% level, whilst the term structure at the 5% level. Notice this time, adjusted R-squared are much higher due to the time-effects. The last column of the table contains the Wald's Chi-squared test. In this test we have only included the factor-parameters and not the time effects. Thus, under the null hypothesis, premia associated with the observable factors are jointly equal to zero. In contrast with our findings in subsection 6.1 of our main methodology we did not find a significant premium for technology factor.

As we have already found two structural breaks, one on March 2010 and the second on April 2013, we have divided the period into three subperiods. The first subperiod (see the two regressions in Panel B) starts from January 2005 and ends on February 2013. In the first subperiod we found positive premia for *UIP*, *UINF* and *UTG* and a negative premium for *UDP*. For the remaining two factors (*ΔTERM* and *UEPU*) we neither found significant premia, nor these variables helped increase the predictive power of the model. In the second regression of Panel B, we substituted innovations on technology sector with the restricted shocks which were derived from equation (6.4.2) and presented in subsection 6.4. Using the restricted shocks, we could not find a statistically significant premium for technology factor at any conventional level as the p-value was 11.42%.

The fact that premia for technology factor were now insignificant, do not give further support that could count as an additional risk on the pricing models, and thus we should be suspicious that its relevant innovations just concur with innovations on other variables or it may be the case where technology is a significant source of risk but factors like industrial production already count this risk. We may examine the effects of the financial crisis of which time horizon is included in the first subperiod separately later on.

The second subperiod consists of all months from March 2013 (where the first structural break was observed) through March 2013 (see Panel C). We found premia for two factors only, which were significant at the 1% level. The first one is the slope of the yield curve and the second one is the technology factor. Notice that the term-structure has now a positive premium. When the slope of the yield curve increases, the market anticipates higher aggregate production growth rates. This finding is consistent with the premia of Chen et al. (1986) and Chan et al. (1985). Obviously, we have also included three more factors in the model, *UIP*, *UINF* and *UDP* even if they seem to have no significant premiums because their inclusion has increased the predictability of the model. Again, we substituted innovations for *UTG* with the restricted shocks of technology factor and found that the monthly premium was still significant at the 1% level. These results lend support to the arguments that we should regard technology factor as a systematic force in the stock market.

Finally, the third subperiod starts from April 2013 (where the second structural break was observed) and ends with the last month of the entire sample period, that is, December 2017. Only industrial production seems to have a significant premium throughout this period but the inclusion of term-structure factor improved the predictability of the model. The coefficient for *ΔTERM* is not statistically significant at any conventional level. To explore in more depth the relationship between the risk factors and stock returns we further implemented panel regressions for several other subperiods and observed the sign of *ΔTERM* and *UINF* was quite sensitive to the subperiod of interest. From one aspect, testing for premia through a large period ensures more reliable results as more observations are used in the analysis. On the opposite, an analysis into subperiods has a major advantage: we can assess whether this relationship changes through time.

To assess the effects of the financial crisis we split the first subperiod into further subperiods. In Table 6.6 we present the results of monthly premia for three subperiods. In Panel A we test for priced factors for the subperiod from January 2005 through November 2007 a period which precedes the recession. The results indicate that Industrial production factor had a negative premium, significant at the 10% level (p-value: .075). We attribute the negative premium to the fact that stock markets were falling due to the negative effects of mortgage loans whilst Industrial Production index was increasing and thus, stocks of which prices were following the index were more valuable. The risk associated with changes of default premium on bond markets, *UDP*, was also negatively priced at the 1% level. Obviously, investors would demand a higher compensation to hold equity on those companies of which stock prices were experiencing dramatic falls when uncertainty was increasing.

In addition, the term-structure factor, *ΔTERM*, was positively priced at the 1% level. The steepening yield curve is “good” news to investors according to expectations hypothesis and thus the positive premium is interpreted as agents required a compensation for those stocks which were positively correlated with the slope of the yield curve for the risk of flattening yield curve.

In Panel B we further test for priced factors for the subperiod from December 2007 when the US recession starts through February 2010, a month which precedes the first structural break we observed. Obviously, this subperiod captures the entire period of recession which lasts until June 2009. Based on the first regression of Panel B, all factors except for technology growth had a significant premium. Industrial production had normally a positive premium at the 1% level. Companies of which stock prices were positively correlated to aggregate growth of production would compensate investors. There was also a positive premium for inflation at the 5% level. Apparently, the economy was not experiencing inflationary pressures and in fact, a positive shock of inflation could hypothetically serve as an indication of growing paces of the aggregate activity which was appealing to stock markets during this period. *UDP* had again a negative premium, as expected, but it was estimated to be significant at the 10% level (p-value: .073). Notice also, that *ΔTERM* was now negatively priced at the 10% level (p-value: .065). During the financial crisis interest rates had a downward trend, and the short-term 3M rates saw a dramatic dive to almost zero on December 2008 and thereinafter. One of the concerns over the crisis was the risk that the Quantitative Easing by the Fed could dynamically bring inflation in the long-run in the worst-case scenario where the excess liquidity in the markets would not be absorbed into investments. Thus, an increment of the Long rates would hide increased premia for expected future inflation and would be “bad” news for investors. As have already described, when positive shocks bring “bad” news, premia should be negative. Policy-related uncertainty also seems a priced factor during this period with a negative and statistically significant premium at the 10% level. Consistent with the findings of Baker, Bloom and Davis (2013) during the financial crisis increases on EPU index coincide with intensive fluctuations on stock markets. The more uncertain the economic environment due to policy affairs the more compensation investors would require. The negative premium indicates that investors would require higher returns on stocks whose prices fall in times of intensive uncertainty.

In the second regression of the same panel we have substituted innovations of policy uncertainty with the restricted shocks derived by equation (6.4.1) of subsection 6.4 to further examine if policy related shocks that do not coincide with shocks of *UDP* and *ΔTERM* are still priced. Based on the estimated coefficients, policy related premium turned into insignificant. Therefore, we cannot reject the null hypothesis that the two bond-market related factors, *UDP* and *ΔTERM*, already capture the effects of policy uncertainty. In this case, we claim there are no strong indications that a policy related factor should be included in the pricing model as an additional factor. In the third regression of Panel B only the first four factors have been included in the model. Based on the results, without the policy-related factor, significance of the premia for *UDP* has improved from 10% to the 5% level.

Finally, in Panel C we present our findings when the testing period of panel analysis starts from January 2005 and ends on June 2009 when the US recession is over. During this period, the best model in terms of predictability is the one consisting of *UIP*, *UINF*, *UDP* and *UTG*. We have already described the signs of the former three factors and there are no surprises on these results. *UTG* is now priced (with a p-value: .0577) in contrast with the findings on altered subperiods of Panels A and B. In a more rigorous test, (see second regression of Panel C) we substituted shocks of technology growth with the restricted shocks for this factor, derived from equation (6.4.2), a technique presented in the subsection 6.4. The magnitude of technology-related premium was slightly reduced but was still significant at the 10% level. Therefore, these results further support that technology growth was a systematic source of risk.

To summarize, in this subsection we implemented additional tests to derive risk premia into subperiods, allowing beta coefficients to change every month. We provide evidence that the derived prices are quite sensitive to the period we set each time, revealing the construction of a pricing model and its appropriateness to predict stock prices is quite hard in practice. At least, this technique could provide further tests to estimate for pervasive influences that caused stock prices fluctuations within the period we tested. We could not corroborate these findings when different portfolio formations implemented and thus one could not use this technique as a forecasting tool. On the opposite, our main methodology seems robust on alternative portfolio formations.

Table 6.6

This table reports the estimated monthly risk premiums for three subperiods (one related to a short-period preceding the financial crisis, one which involves the financial crisis and ends on an observed structural break and one which captures all months from 2005 through the end of the crisis). For all panel regressions we used time-fixed effects models with white period S.E and the dependent variables were monthly excess returns of **30 portfolios arranged by the securities' exposure to market risk**. Regressors are factor loadings of which values change per month. Each Panel (A to C) reports the derived premiums for different testing periods. In every Panel only the results on the "best model" (in terms of within-the-sample forecastability) are shown. That means, for every testing period, starting with a set of six factors (UIP, UINF, UDP, ΔTERM, UEPU and UTG) we removed progressively one-by-one factors of which (1) their relevant premiums were statistically insignificant and (2) their inclusion could not increase Adjusted R-squared. We define the "best model" as the one consisting of factors which improve Adj. R^2. Whenever *UEPU* or *UTG* appears significant, another regression was run where their realizations were substituted by ϑ_{EPU} and η_{TG} respectively (restricted shocks on policy uncertainty and tech-factor, see equations 6.4.1 and 6.4.2) to corroborate their significance. Numbers in bold denote estimated coefficients (i.e. risk premiums), numbers in parentheses are the standard deviations and numbers in square brackets are the t-statistics. Three stars (***) indicate significant values at the 1% level, two stars (**) at the 5% level and one star (*) at the 10% level respectively. The last three columns report the adjusted R-squared, the Durbin Watson (DW) test for serial correlation on residuals and the Wald-statistic of which under the null hypothesis premiums for all factors (jointly) equal to zero. Wald tests are chi-square statistics with K degrees of freedom where K is the number of factors (we have not included the time effects).

Const.	UIP	UINF	UDP	ΔTERM	UEPU	ϑ_{EPU}	UTG	η_{TG}	Adj. R^2	DW	Wald
Panel A			Subperiod:		[01/2005 - 11/2007]				Panel Observations:		1,050
0.00204	**-0.00174**		**-0.00016**	**0.00113**					0.6925	2.11	26.5
(0.00083)	(0.00098)		(0.00004)	(0.00034)							
[2.47]	[-1.78]		[-3.63]	[3.32]							
**	*		***	***							
Panel B			Subperiod:		[12/2007 - 02/2010]				Panel Observations:		810
-0.02752	**0.01020**	**0.00295**	**-0.00073**	**-0.00263**	**-0.12039**				0.8082	2.04	39.27
(0.00367)	(0.00237)	(0.00150)	(0.00040)	(0.00143)	(0.07106)						
[-7.49]	[4.31]	[1.97]	[-1.80]	[-1.85]	[-1.69]						
***	***	**	*	*	*						
-0.02679	**0.00987**	**0.00304**	**-0.00071**	**-0.00236**		**-0.08202**			0.8083	2.05	40.90
(0.00350)	(0.00233)	(0.00146)	(0.00041)	(0.00139)		(0.06646)					
[-7.66]	[4.24]	[2.09]	[-1.74]	[-1.70]		[-1.23]					
***	***	**	*	*							
-0.02599	**0.01059**	**0.00284**	**-0.00095**	**-0.00227**					0.8076	2.05	35.21
(0.00351)	(0.00236)	(0.00135)	(0.00046)	(0.00126)							
[-7.41]	[4.49]	[2.11]	[-2.09]	[-1.81]							
***	***	**	**	*							
Panel C			Subperiod:		[01/2005 - 06/2009]				Panel Observations:		1,620
-0.01013	**0.00388**	**0.00098**	**-0.00043**				**0.00068**		0.7904	2.03	36.86
(0.00106)	(0.00116)	(0.00043)	(0.00010)				(0.00036)				
[-9.57]	[3.36]	[2.26]	[-4.40]				[1.90]				
***	***	**	***				*				
-0.00985	**0.00371**	**0.00102**	**-0.00037**					**0.00051**	0.7903	2.02	34.56
(0.00102)	(0.00113)	(0.00045)	(0.00009)					(0.00031)			
[-9.67]	[3.27]	[2.27]	[-4.11]					[1.66]			
***	***	**	***					*			

Section 7. «Caveats and Future Research»

All Fama and MacBeth (1973) two-pass variant procedures which have been used extensively in the literature to estimate risk premia are sensitive to an *errors-in-variables problem*. This problem arises as the sensitivities of securities are estimated with the provision of time series regressions and are thus estimated coefficients, not the true parameters. Since we do not know the true parameters it is quite difficult to measure the extent of the problem. To mitigate this problem, we have arranged all securities in our sample into portfolios. A portfolio of stocks is more possible to restrict these errors which distort the results. This solution was initially suggested by Fama and MacBeth (1973) and further implemented by researchers who used the two-pass procedure. McElroy and Burmeister (1988) also suggested another technique of nonlinear regressions to derive estimates of both the premia and betas without being exposed to errors-in-variables and thus, without requiring any securities classification into portfolios.

A further problem in this study is related to the *survival bias*. To form our sample, we required stocks have no missing observations during the period between December 1999 and December 2017. There are many advantages with this requirement. At first, we obtained a more manageable sample and further we let the portfolios maintain the number of constituent securities. Otherwise, there would be periods with a greater and periods with a smaller number of securities. This restriction allowed us to code the procedure more easily. Apparently, many firms that went bankrupt before December of 2017 have not been included in our sample, same as firms listed in any US stock market after December of 1999. Moreover, we removed firms which were found to expose outlying data as outliers distort the results. If the returns on stocks of the sample do not represent the common reactions in the US stock market during this period, then we face the problem of survival bias. Fortunately, given that our analysis is in a shorter sample period than other studies and the fact that we have maintained a large number of stocks in our sample, that is 1,161 stocks, we estimate our sample is adequate enough. In addition, we repeated the tests of the main methodology we suggested using portfolios constructed by Kenneth R. French and corroborated our findings. Essentially, we obtained series of monthly returns for 10 portfolios sorted by size and 25 portfolios sorted by size and momentum from the website of Kenneth R. French and both types of portfolios gave consistent premia in terms of signs and significance. Thus, we conclude our sample of selected stocks could stand as a representative sample.

As in all multifactor models with observable factors, especially in the APT framework, where the factors have not been specified by the theory, we should be concerned about any *omitted variables* before presenting any conclusive result. Omitted variables are known to give spurious results. Problems such endogeneity and autocorrelation arise when not all true factors are included in the model, or when the factors do not have a linear relationship with the dependent variable. Asset pricing models are also restricted by nature when dealing with these problems. For instance, the basic APT equation is specific, and one should not add lagged values of residuals to mitigate such problems. An arbitrage pricing model requires the regressors to be the factor loadings, that is the sensitivities of returns on shocks occurred by the several factors. As the factors are unknown, we presume these problems obstructed all previous attempts to define them. Furthermore, as there is no information about their identity, we should be cautious that the findings should fit with theory because in many cases the results are *spurious*. To limit the problem of omitted variables in our test models, we tried out to include an unobserved factor, the residual market risk as proposed by Burmeister and Wall (1986). As in their work, we defined residual market risk as the portion of returns on S&P500 not explained by the other (observable) variables. Unfortunately, this attempt proved to be unsuccessful, as the factors did not reveal premia consistent with the theory and thus decided to exclude it. In our main methodology, we obtained annual risk premia estimates with the Generalized Least Squares panel method with white covariance estimators as we observed that the residuals were serially correlated and heteroskedastic. In our alternative methodology, presented in subsection 6.5, we run time-fixed effects models to estimate monthly premia. With the inclusion of time dummies we were not exposed to serial correlation problems and in order to get reliable estimates with the presence of heteroskedasticity across time we used white period standard errors.

In this study we examined whether six variables are associated with risk premiums in the US stock markets for a period of 13 years. Although literature has evolved, more research is to be done in this area. It would be interesting to test a similar model in quite larger period and re-examine both the premia and factor loadings, test for additional candidate factors, or to use even better proxies for these factors. The testing period could also be not representative, even if we have (hopefully) given good interpretations about the signs of risk premiums.

In addition, we isolated the unanticipated components of the variables with the provision of ARMA models assuming investors discount events on macroeconomic indices with such models and that the coefficients as well as the number of orders of autoregressive and moving averages remain stable over the entire sample period. The assumption of stable coefficients is restrictive. If this is not the case, then estimations about shocks could potentially differ significantly from historical shocks and thus these factor realizations could not drive to representative factor loadings and premiums. Even if Gretl, the program we run all ARMA models, reports to run a Kalman filter technique in order to estimate coefficients of ARMA models behind the scenes, residuals of these models still remain an econometric approach to proxy for innovations, sometimes far beyond the realized macroeconomic shocks.

Furthermore, in a future study, we could adjust the code presented in Appendix A so as to let the number of securities vary within the sample through the passage of time. Specifically, the sample would increase whenever new companies are listed in the secondary market and shrink when companies go bankrupt allowing the user to consider an even more representative sample. Such an effort should of course be accompanied by rigorous confirmatory tests to corroborate that portfolios maintain their attributes. If we allow these companies to enter our model without adjusting this code, during months where the securities' monthly returns equal to zero (due to non-existence) the code would give equal weights to these zero values and thus portfolio returns would be spurious.

Section 8. «Conclusion»

We have tested whether four macroeconomic variables of which an extensive literature has suggested to influence stock returns in the US (i.e. see Chen et al. (1986), Chan et al. (1985)), namely industrial production, inflation, default spread and the term structure, still count as pervasive forces for the period from 2005 through 2017. We also assessed whether policy uncertainty and developments in tech-sector further explain variations of stock returns. To obtain the unanticipated components of the variables (i.e. factor realizations as Arbitrage Pricing Theory suggests), we estimated the residuals of ARMA models in contrast to many previous studies which simply use a "first-differences" or a "rate of change" approach or the residuals from simple autoregressive models as we found their techniques could not isolate the unexpected components efficiently and thus agents could forecast part of their series. To test whether investors are systematically compensated when undertaking risks inherent to the specified factors we have implemented a Fama and MacBeth (1973) variant technique where the second-pass (cross-sectional) tests were substituted by a panel data analysis. This approach allows us to test both the model and detect priced risk factors within short periods of time. Interestingly, an assumption such that the time observations should exceed the number of assets tested is not required as in the model proposed by McElroy and Burmeister (1988), though an errors-in-variables problem is not avoided and thus an arrangement of securities into portfolios is required. We further tested if the results are robust when the criterion of securities arrangement into portfolios has changed, an issue addressed by Clare and Thomas (1994).

Regarding the main methodology we suggested, we let factor loadings vary across the calendar years in the sample and derived annual premia via a panel data analysis, assuming these premia remain stable throughout the testing period. Overall, we found investors require compensations (find appealing) to hold stocks of which returns are positively (negatively) related to shocks of industrial production growth, inflation and developments in technology sector and/or stocks of which returns are negatively (positively) related to shocks of the two bond-market factors, namely default premium and term structure of interest rates. In addition, based on our sample, we could not derive a risk-premium inherent to policy uncertainty and thus could not reject the null hypothesis that the two bond-market factors already capture this risk, if any. To corroborate these findings, we run the two-pass procedure with three alternative techniques of portfolios formation under which securities have been arranged by their exposure to market risk, their market capitalization and industry respectively. The three alternatives in general concluded to the same premia in terms of sign and significance with the only exception that under the tests of firm size-sorted portfolios, default premium was not a significant factor.

In sequence, we restricted shocks of policy uncertainty and technology growth factors so as to not coincide with shocks on the four factors proposed by Chen et al. (1986) to further support our arguments and found premia consistent with our main tests. The intuition behind the premia is the following. Stocks of which prices move in the same direction with aggregate production compensate investors for the potential damaging effects of a downturn. As for technology factor, the positive premium fits with the findings of Hsu and Huang (2010). They argue that small high-tech firms have higher returns due to their higher positive sensitivities to technology prospects and small growth firms cut dividends to raise investments when technology prospects are bright, resulting in lower returns. The spread on Corporate bond yields increases in periods of intensive uncertainty and investors would want to hedge against shocks which trigger uncertainty. Investors would require a higher compensation to stocks experiencing dramatic falls in periods of higher uncertainty. Indeed, the negative premium in conjunction with the negative default betas result in positive contributions to expected returns.

The negative premium for the spread on government bond yields implies that investors would want to hedge against the negative effects of rising long interest rates and the positive premium for inflation comes in contrast to the findings of Chen et al. (1986). To explore more in depth any effects of the financial crisis we altered our proposed methodology allowing factor loadings to change per month and further derived monthly premia within subperiods, still assuming these premia remain stable across the time of interest. We found that the estimated monthly premia were quite sensitive to the subperiod we set and to the technique employed to form portfolios, though we present evidence only relevant to the CAPM beta-sorted portfolios as they have achieved a better spread on returns and (presumably) an adequate diversification. Under this technique, we found that the positive premium for inflation emerged from the US financial crisis of 2007-2009. In this non-inflationary environment, a positive inflation signal was not bringing “bad” news to investors but rather a slight increase of the prices in economy would be perceived as good news for aggregate production. During this period, short-term rates plunged to almost zero and it is the long-term treasuries which caused the slope of the yield curve to fluctuate. After the financial crisis the US has experienced the longer expansion of its modern economic history with a downward trend on interest rates. We attribute the negative premium for term structure to the fact that an unexpected increase of long-term rates would render funding costlier for firms and managers would have incentive to suspend borrowing until these rates fall. Investors would require higher returns for those stocks of which prices fall to announcements of increasing long-rates. Even more, investors would find appealing to hold stocks of which returns are inversely related to long bond portfolio returns when shocks of long interest rates occur. To interpret the positive premium for interest rates spread within subperiods just before and after the crisis we lend arguments of expectations hypothesis, based on which, a steeper (flattening) slope indicates brighter (worsen) economic prospects. Conflicting premia for the term-structure spread in different testing periods have long been observed by the work of Ammer (1993).

To conclude, risks inherent to industrial production, inflation, default premium, term-structure and technology could explain almost one third of the variation of annual returns in the US of 2005-2017 and could enter an asset pricing model with non-arbitrage arguments.

Appendix A

A.1 Coding the procedure of portfolios formation

In this Appendix A we present a code constructed in Matlab software which, given a number of input data, estimates each security's period by period returns and constructs three types of portfolios, one depending on the securities' firm size, one on the simple CAPM beta estimates and one depending on the industry of each security. We may devote this subsection to describe, in short, the procedure this algorithm follows, its input requirements and finally the output data. For this code we primarily need a file (i.e. excel worksheet), which contains series of end-of-period prices per share, dividends per share and market capitalization for each security in our sample. Henceforth, for this subsection only, suppose *T* denotes the number of time observations (in our sample *T*=216 as the sample period from January 2000 through December 2017 is composed by 216 months), *N* the total number of securities (in our sample *N*=1,161) and *Nind* the total number of industries.

Input data

To run this code, one needs the following inputs:

1. **SEC**: Is the file which contains information relevant to the securities in our sample. We may illustrate this file as a matrix of *T+1* x *Nx3* size, where for for each security it devotes 3 columns. The first column is the end-of-period (adjusted) price per share, the second column is the end-of-period dividends per share (annualized)[30] and the third column is the end-of-period Market Value of Equity. The adjacent three columns are relevant to the second security in our sample, and so on, until the last three columns refer to the Nth security. The file contains *T+1* rows, as we also need information relative to the last month prior of our sample's period (in our study, December 1999) to calculate returns for the first month. We also need the end of previous-year market value of equity (in our sample, December 1999) to arrange securities based on their size for the first calendar year in our sample (i.e. 2000). Consequently, for this study, the first row of SEC refers to end-of month data for December 1999, the second row refers to January 2000, and so on, where the last row (*T+1*) refers to December 2017. If one is interested to construct industry portfolios, it is important that securities have been arranged based on their industry (regardless the number of securities an industry has). That is, if we have data for say *k* securities in the first industry of interest and *y* securities in the second industry of interest, it is a compulsory that the first *k*x3 columns of SEC are referred to the first industry's securities and the adjacent *y*x3 columns contain information about the second industry's securities.

[30] The code will consider the monthly equivalent dividends per share by just dividing the annualized dividends by 12.

2. **MKTIND**: Is a column vector of *T+1* elements with the end-of-period values of a market index. In our sample we use S&P 500 index values. The first element contains the end-of December 1999 value of S&P 500 (a requisite to calculate the market index returns for the first month in our sample), the second element is the end-of-month value of January 2000, and so on, until the *T+1* element represent the value at the end of December 2017.
3. **SpI**: Is a *Nind* x *2* matrix where the first column represents the number of each industry in our sample (i.e. 1 is referred to the 1st industry, 2 is referred to the 2nd industry and Nindth to the last industry) and the second column has the number of (sample) securities included in each industry. For instance, if the first industry has *k* securities and the second has *y* securities, then the first row of this matrix contains the elements [1, k] and the second the elements [2, y]. Apparently, this requires that the first k securities in **SEC** are those related to industry of number 1 (thus the first *k*x3 columns are relevant to the first industry) and the adjacent y securities are related to industry of number 2 (thus the adjacent *y*x3 columns are relevant to the second industry).
4. **Rf**: Is a column vector of *T* elements with the values of the risk-free rate per month. We used the annualized 3-Month T-Bill rate and obtained the monthly equivalent as a proxy for the risk-free rate. In our study, the first element contains the rate relative to month January 2000, whilst the last element contains the rate of December 2017. You may notice that the time observations are now *T* and not *T+1* as the rate of December 1999 is not needed.
5. **rm**: Is the number of observations we need this code to exploit in each regression when we derive the CAPM beta of each security to arrange them in ascending order and form portfolios. In our study, we required for each month a securities' re-arrangement in ascending order based on securities' beta exploiting five years of data prior to the month of re-arrangement. Since we have monthly observations in our data, 5 years data equals to 60 months and therefore, we set rm=60. This means that for each security, the first 60 monthly excess returns (from January 2000 through December 2004) will be regressed with the first 60 monthly excess returns of S&P 500 to give the first beta estimates and further form portfolios and estimate the portfolio returns up to month January 2005. Then the code will run forward a month and run the same regressions (with rm=60 time observations) for the period between February 2000 and January 2005 to derive all securities beta estimates, re-arrange them, change the synthesis of portfolios (if necessary) and calculate the portfolio returns for the month February 2005. The same procedure will then be repeated for the entire period.
6. **NPort**: Is the number of portfolios we require the code to construct. The same number of portfolios is constructed for both the MVE-sorted and the beta-sorted portfolios. In our study we set NPort=30. Notice that given the number of securities *N* does not change in our sample, the more portfolios we wish to construct, the fewer securities each portfolio will contain. Thus, there is a trade-off between diversified portfolios and the number of portfolios (cross-sectional observations) we will obtain for our regressions.

Algorithmic Procedure

This code exploits all input data and forms portfolios based on different characteristics of securities. The first stage is rather simple as the code calculates monthly (natural logarithmic) returns for each security and obtains the market capitalization values of interest for a further analysis. Since we need the MVE-sorted portfolios re-arrangement of securities occur at the beginning of each calendar year based on the end-of-previous-year reported market capitalization of each security, we do not need all elements of the monthly series of market capitalization. At its second stage, the code estimates the beta coefficients of each security derived by simple CAPM (OLS) regressions on a rolling-forward-one-month basis using **rm** observations as set in the input data. Hence, for each security, a beta coefficient series is derived with T-rm+1 elements as we do not have beta coefficient observations for the first rm-1 months. On the third stage, securities are classified each year based on their market capitalization as reported at the end of previous year for MVE-sorted portfolio returns computational purposes in a further step. On the fourth stage, securities are classified, based on their reported market beta coefficient estimates. The beta estimations of the first series of CAPM regressions will be considered to arrange securities returns for the first rm+1 months, whilst any further cross-sectional betas will be used to re-arrange securities for the next month only.

The fifth stage consists of MVE-sorted portfolios construction. In our study, since we had 1,161 securities in the sample file and required 30 portfolios, the number of securities per portfolio is not an integer (1,161/30= 38.7). In this case the code reads 38 securities per portfolio and starting from the first portfolio it adds one more security and runs to the adjacent portfolio to add one more security until the sum of securities included in all portfolios equals the total number of securities in the sample. That is why Tables (5.2) and (5.3) present the first 21 portfolios having 39 securities and the remaining 10 including 38. In every case where, based on the input data, the resultant securities per portfolio in not an integer, the code will add progressively the stocks into portfolios to ensure that the number of securities across portfolios will differ by at most one security and all securities in the sample will be classified within a portfolio. Each portfolio adds and drops out securities at the beginning of each year whenever changes in the firm-size arrangement occurs but the total number of securities each portfolio has per annum does not change. All portfolios are equal weighted. Portfolios are sorted in ascending order, which means every time the first portfolio contains the securities of the smallest size whilst the last portfolio is consisted of securities with the largest size.

In the sixth stage, a similar procedure of the fifth stage is implemented, but this time portfolios are being constructed based on securities CAPM betas. The difference is that the portfolios add and drop securities every month after the rm+1 months as in the fourth stage we set the rearrangement of securities occur each month. All portfolios are sorted in ascending order based on their exposure to market risk and use equal weights to calculate their monthly returns.

The seventh and last stage of the code is related to portfolios construction based on the securities industries. Thus, securities are sorted only once based on their industry and equal weighted portfolios are constructed. The number of portfolios equals the number of industries and each portfolio contains a different number of securities. We have required though portfolio industries with less than 10 securities included in, to be removed. Thus, this technique of portfolio formation will not necessarily exploit all securities in the sample. This restriction can easily be modified or even removed by the user.

Output data

The main Output data are the following matrices:

1. **SECRET**: Is a *T*x*N* matrix of all securities returns. The securities are sorted exactly as in the **SEC** of input data and all columns display the series of monthly returns. Elements of the first row are associated with the returns of the first month in the sample (January 2000 in our study), whilst the T^{th} row contains all securities' monthly returns of the last month in the sample (i.e. December 2017). If one is interested to obtain the excess securities returns, should replace it with **EXCESSRET** in the output arguments (first line of the code).
2. **PORTBET**: Is a *T*x*NPort* matrix of the beta-sorted portfolio returns. Portfolios have been arranged in ascending order based on their exposure to market risk. The first column represents the series of returns of the portfolio with the lowest exposure and the $NPort^{th}$ column represents the monthly returns of the portfolio with the highest exposure.
3. **PORTMV**: Is the corresponding *T*x*NPort* matrix of the MVE-sorted portfolio returns. The first column represents the series of returns of the portfolio with the smallest market capitalization stocks and the $NPort^{th}$ column represents the monthly returns of the portfolio with the largest market capitalization stocks.
4. **PORTIND**: Is the *T*x*Nind* matrix of the monthly industry portfolio returns. Industry portfolios have been sorted according to the **SpI** input file. That is, the first portfolio (first column) is related to the industry of number 1, whilst the $Nind^{th}$ portfolio (last column) is related to the latest industry.
5. **INDEXRET**: Is a column vector of the T monthly returns on the market index. If one is interested to extract the monthly excess returns, should replace it with **EXCESSINDX** in the output arguments (first line of the code).

Obviously, in this study we needed the **PORTBET**, **PORTMV** and **INDEXRET** matrices as input data in the code presented in Appendix B which is related to our main methodology. Additional output data can be extracted if requested in the output arguments of the code in the first line either for further computational purposes or for confirmation purposes as the code produces more matrices[31].

[31] These matrices are visible throughout the main body of code (i.e. SECMV, SECBET, Spp, Spp3, SORTMV, SORTMVRET, SORTBET, SORTBETRET, EXCESSRET and EXCESSINDX). SECMV is a matrix containing only the Market Value of Equity for each security at the end of each year (i.e. Dec 1999 to Dec 2016, Dec 2017). SECBET contains the simple CAPM beta coefficients of all securities. Spp is a vector of the number of securities per portfolio for the two

A.2 The Code

```
function [SECRET,PORTMV,PORTBET,PORTIND,INDEXRET] =
taiportform(SEC,MKTIND,SpI,Rf,rm,NPort)
%This code was constructed by Symeon Taipliadis as a part of his thesis.
%Last Update: 12.19.18. New updates may exist.
%For related questions please contact to s.taipliadis@gmail.com
%As a guide see Appendix A and subsection 5.2.
%SEC matrix contains 3 columns per security: [P,DPS,MV].
%rm: Months required for each regression.
%SpI: Securities per Industry. Industry number at (:,1),
%number of Securities per industry at (:,2).
%SEC and MKTIND have T+1 rows (1st value for 12/94 to calculate Returns)
%Rf has T rows.
T=length(SEC(:,1)); %T: Number of months.
NSample=length(SEC(1,:)); %NSample: Number of Columns.
N=3\NSample; %N: Number of securities in the sample.
%%
%SECRET: Securities Returns (T,N)
%SECMV: Securities Marker Value of Equity at the end of previous year (Y,N)
%SECBET: Securities (Market) Betas (Y,N)
T=T-1; %We do not have returns for the 1st observation.
Y=T/12;
SECRET=zeros(T,N);
SECMV=zeros(Y,N);
k=1;
for j=1:+3:NSample-2
    for t=1:T
        SECRET(t,k)=log((SEC(t+1,j)+(SEC(t+1,j+1))/12)/SEC(t,j));
    end
    k=k+1;
end
k=1;
for j=3:+3:NSample
    p=1;
    for y=1:Y
    SECMV(y,k)=SEC(p,j);
    p=p+12;
    end
    k=k+1;
end
%%
%Market Betas Estimation for each security.
INDEXRET=zeros(T,1);
SECBET=zeros(T,N);
for t=1:T
    INDEXRET(t,1)=log(MKTIND(t+1)/MKTIND(t));
end
EXCESSRET=zeros(T,N);
EXCESSINDX=zeros(T,1);
for t=1:T
    EXCESSINDX(t)=INDEXRET(t)-Rf(t);
```

types of portfolios PORTMV and PORTBET. Spp3 is the number of securities per industry portfolio (industries with less than 10 securities are not presented here, since these industry portfolios have not been constructed).

```
    for i=1:N
        EXCESSRET(t,i)=SECRET(t,i)-Rf(t);
    end
end
%Regressions on Market Index.
BETAS=zeros(T,2,N);
%Y=EXCESSRET;
XVARS=[ones(T,1) EXCESSINDX];
for i=1:N
    p=0;
    for t=rm:T
        p=p+1;
        BETAS(t,:,i)=(XVARS(p:t,:)\EXCESSRET(p:t,i))';
    end
end
%MKTRES=zeros(T-rm+1,N);
%for i=1:N
    %MKTRES(:,i)=EXCESSRET(rm:T,i)-XVARS(:)*BETAS(:,:,i)
%end
for t=1:T
    for i=1:N
    SECBET(t,i)=BETAS(t,2,i);
    end
end
    %BETAS contain Alpha coeff (t,1,N) and Market beta coeff (t,2,N).
    %We only need Market beta coeffs.
%%
%Returns Classification based on Securities' MV.
%Each year securities are classified in ascending order based on their MVE
%reported at the end of previous year.
SORTMVRET=zeros(T,N);
SORTMV=zeros(Y,N);
p=0;
for y=1:Y

 for t=1:12
    Temp=zeros(N,2);
    for i=1:N
        Temp(i,1)=SECRET(p+t,i);
        Temp(i,2)=SECMV(y,i);
    end
    SortTemp=sortrows(Temp,2);
    for i=1:N
    SORTMVRET(p+t,i)=SortTemp(i,1);
    end
 end
    for i=1:N
         SORTMV(y,i)=SortTemp(i,2);
    end
   p=p+12;
end
%%
%Returns Classification based on securities’ simple CAPM beta.
%Each month (t) securities are classified in ascending order based on their,
%Market beta.
SORTBETRET=zeros(T,N);
SORTBET=zeros(T,N);
```

```
%Initial rm+1 months: Securities are classified by the 1st regression.
%After rm+1: Securities at t are classified in a monthly basis by their
beta(t-1).
Temp=zeros(N,rm+2);
for t=1:rm+1
    Temp(:,t)=SECRET(t,:);
end
Temp(:,rm+2)=SECBET(rm,:);
SortTemp=sortrows(Temp,rm+2);
SORTBET(rm+1,:)=SortTemp(:,rm+2);
for t=1:rm+1
    SORTBETRET(t,:)=SortTemp(:,t);
end

for t=rm+2:T
    Temp=zeros(N,2);
    for i=1:N
    Temp(i,1)=SECRET(t,i);
    Temp(i,2)=SECBET(t-1,i);
    end
    SortTemp=sortrows(Temp,2);
    for i=1:N
    SORTBETRET(t,i)=SortTemp(i,1);
    SORTBET(t,i)=SortTemp(i,2);
    end
end
%%
%Portfolios formation (PORTMV) based on Securities' MVs.
Spp=zeros(1,NPort); %Spp=Securities per portfolio.
if (NPort\N)==round(NPort\N)
    Spp(:)=NPort\N; %Each portfolio has an equal number of securities.
elseif (NPort\N)<round(NPort\N)
    Spp(:)=round(NPort\N)-1;
elseif (NPort\N)>round(NPort\N)
    Spp(:)=round(NPort\N);
end
p=1;
while sum(Spp(:))<N
    Spp(p)=Spp(p)+1;
    p=p+1;
end
PORTMV=zeros(T,NPort);
srtpnt=0;
endpnt=0;
for p=1:NPort
    srtpnt=endpnt+1;
    endpnt=srtpnt+Spp(p)-1;
    for t=1:T
        PORTMV(t,p)=mean(SORTMVRET(t,srtpnt:endpnt));
    end
end
%%
%Portfolios formation (PORTBET) based on Securities' CAPM Betas.
%Again the same procedure.
Spp=zeros(1,NPort); %Spp=Securities per portfolio.
if (NPort\N)==round(NPort\N)
    Spp(:)=NPort\N; %Each portfolio has an equal number of securities.
```

```
elseif (NPort\N)<round(NPort\N)
    Spp(:)=round(NPort\N)-1;
elseif (NPort\N)>round(NPort\N)
    Spp(:)=round(NPort\N);
end
p=1;
while sum(Spp(:))<N
    Spp(p)=Spp(p)+1;
    p=p+1;
end
PORTBET=zeros(T,NPort);
srtpnt=0;
endpnt=0;
for p=1:NPort
    srtpnt=endpnt+1;
    endpnt=srtpnt+Spp(p)-1;
    for t=1:T
        PORTBET(t,p)=mean(SORTBETRET(t,srtpnt:endpnt));
    end
end
%%
%Industry Portfolio formation (PORTIND).
Nind=length(SpI(:,2)); %Nind: Number of Industries.
Temp=zeros(T,Nind);
srtpnt=0;
endpnt=0;
for ind=1:Nind
    srtpnt=endpnt+1;
    endpnt=srtpnt+SpI(ind,2)-1;
    for t=1:T
        Temp(t,ind)=mean(SECRET(t,srtpnt:endpnt,1));
    end
end
%We may remove portfolios with less than 10 securities in their industry.
sumip=0;
for ind=1:Nind
    if SpI(ind,2)>=10
       sumip=sumip+1;
    end
end
PORTIND=zeros(T,sumip);
k=1;
Spp3=zeros(2,sumip);
for ind=1:Nind
    if SpI(ind,2)>=10
        PORTIND(:,k)=Temp(:,ind);
        Spp3(1,k)=SpI(ind,1);
        Spp3(2,k)=SpI(ind,2);
        k=k+1;
    end
end

end
```

Appendix B

B.1 Coding the Procedure of the first-pass time series regressions and panel formation (Steps 3 and 4 of the main methodology).

This (second) code was constructed in Matlab software in order to run the first-pass OLS time series regressions of portfolios returns with the candidate factors. Following, there is a brief description of the inputs required, the procedure it follows and the final output. Henceforth, for the following description only, *T* is the total number of time observations in the sample (i.e. total months), *P* is the total number of Portfolios and *K* is the total number of observed factors. The regressors of all regressions become *K+1* when user decides to include the residual market risk (unobserved factor). Residual market risk is the portion of return of a market index (say S&P500) that is not explained by the realizations of observable factors. In case the user includes the unobserved factor, has also the ability to define structural breaks on the regression of the market index to the observable factors. The code does not perform any test on structural breaks and thus breaking points are included exogenously by the user. The user will receive a series of returns of the unobserved factor, just for confirmatory purposes. In addition, he/she will receive two output matrices. The one corresponds to panel data as described in the main methodology and a second is panel data in the form of the methodology described in subsection (6.5). These two panel-form data will be extracted by the user in order to further run panel regressions. The user will also determine the testing period by defining the first *rm* months of the sample that will only be used to derive the first series of betas. The testing period of a total of *T-rm* months is the period being used in the second-pass regressions and hence it is important to distinguish the testing period from the full sample period. In this study the full sample period is [January 2000 – December 2017] and since the first *rm*=60 months (January 2000 – December 2004) will only be exploited to give beta estimates for the first calendar year (or month) of the testing period, the latter period is reduced to *T-rm* months (January 2005 – December 2017).

Input data

To run this algorithm, one needs the following data:

1. **PORTFOLIOS**: Is a *T*x*P* matrix where T is the total number of time observations in the sample (i.e. months) and *P* is the total number of Portfolios. Thus, each column represents the return series of each portfolio. In our study we used the **PORTBET** matrix in our main analysis and the **PORTMV** and **PORTIND** matrices to test the robustness of results, which were the outputs of the first algorithm (see: Appendix A).
2. **FACTORS**: Is a TxK matrix where K is the total number of observed factors we wish to test. For instance, if we have specified two observed factors, then K=2, and each column should contain the monthly realizations of each of the two factors.

3. **INDEXRET**: Is a column vector of monthly returns of a market index and will be used to derive the unobserved factor if user decides to include it in the model. In our study we do not consider the residual market risk since we observed it distorted our results, but the user could easily use the returns series of S&P500 index, as have been calculated by the first algorithm for instance (see: Appendix A).
4. **BREAKS**: To derive series of the residual market risk (unobserved factor) for the entire sample period, the code will regress the returns of the market index with the observed factors' realizations. If there are structural breaks and want the code to take them into account in this regression, a column vector of the breaks is required in the input arguments, otherwise we may just press the zero number and the code will run only one regression for the entire period to derive series of the residual market risk. In case we determine (exogenously) structural breaks, **BREAKS** is a column vector of *tb* scalars, where *tb* is the total number of breaks we have set. Each of these scalars should contain the number of month we have observed a structural break. For instance if there is only one break occurs in January 2003, then *tb*=1 and BREAKS={37} as January 2003 is the 37^{th} month in our sample. The user will have to enter the number of 37 (in this case) and not the number of *tb*.
5. **Rf**: Is a column vector with the series of the risk-free rate, exactly as it is in the first algorithm (see: Appendix A).
6. **rm**: Is the number of months we require the code to exploit in the regressions. In our study, we required a number of 60 observations meaning that with the first five years of data (in our case from January 2000 through December 2004) the code will estimate all portfolios' factor sensitivities and these sensitivities (betas) will be further used as the first observations to explain the annual or monthly returns of 2005, depending on the methodology we implement (main or alternative).
   - As for the output matrix which is related to the main methodology, the code will roll forward one calendar year and then will run time series regressions for all portfolios for the period from January 2001 through December 2005 and obtain their sensitivities which will be used to explain the annual portfolio returns of 2006. The same procedure will be continued for the entire sample period.
   - As for the output matrix which corresponds to the alternative methodology, which was described in subsection (6.5), the code will roll forward one month only and then will run time series regressions for all portfolios for the period from February 2000 through January 2005 to obtain the betas which will be used to explain the monthly portfolio returns of February 2005. The same procedure will be continued for the entire sample period.
7. **unobs**: I takes only two values: {**1**}, if the user decides to include the unobserved factor in the model and {**0**} if the user wants to run the regressions without including the unobserved factor. In our study we have not included the residual market risk in the model.

Algorithmic Procedure

Three stages constitute this code. In the first stage, the code estimates the series of the residual market risk, which can be interpreted as an unobserved factor. In fact, the residual market risk is the returns of the market index (in our study the S&P500) not explained by the realizations of the observed factors. If **FACTORS** in the input arguments is a *T*x*K* matrix, then the residual market risk is simply the residuals of an OLS regression where the dependent variable is the returns on the market index and the explanatory variables are the K observed factors. If further, **BREAKS** in the input arguments has not a zero value then depending on how many breaks we have exogenously determined, the unobserved factor's realizations is a series constituted by the residuals of more than one regressions. For instance, if we have determined a structural break in March 2010 then **BREAKS**={123} as March 2010 is the 123th observation in our sample and residuals from a regression of the first 122 observations will give the first 122 factor realizations of the unobserved factor and residuals from a second regression of all months from 123th through the (last) 216th month in the sample will give the other (missing) factor realizations. If we have determined two structural breaks, one on March 2010 and one on June 2012 (150th month) then **BREAKS** is a column vector of two scalars {123, 150} in the input arguments. In this case three regressions are needed to estimate the unobserved factor realizations. The first regression is related to months 1-122, the second is related to months 123-149 and the third is related to months 150-216. For all three regressions the dependent variable and the explanatory variables remain the same, and only their observations change as the periods of the time series regression changes. The residuals of all three regressions will finally give the series of the residual market risk.

In the second stage the code runs OLS time series regressions to estimate the factor sensitivities for all portfolio returns on all factors. Specifically, starting from the first portfolio, its excess returns for the first *rm* months (in our example for the period between January 2000 and December 2004) will be regressed with the first *rm* realizations of *K* factors (or *K+1*, with K observed and 1 unobserved). The code will then save its estimated sensitivities. These sensitivities are needed to explain (in a later time) the annual portfolio excess returns of the calendar year which follows the rm months (in our case 2005). In sequence, the code will roll forward one calendar year in the sample and run the same regression for the first rm realizations (in our case the period between January 2001 and December 2005). These estimates will then be saved as they are needed (in a later time) to explain the annual portfolio returns for the following year (in our case 2006). The same procedure will be repeated until the last regression (in our case the regression for the period between January 2012 and December 2016) provide the estimated sensitivities which will further be used to explain annual excess returns of the last calendar year in the sample (i.e. 2017). All this procedure described above will be repeated for all portfolios. Up to this point, the algorithm has constructed a matrix with the name **PANELY** and the user can proceed to the panel data analysis, as described in our main methodology.

In the third stage the code runs again OLS time series regressions to estimate the factor sensitivities for all portfolio returns on all factors, but this time, it follows the alternative methodology described in subsection (6.5). Specifically, starting from the first portfolio, its excess returns for the first *rm* months (in our example for the period between January 2000 and December 2004) will be regressed with the first *rm* realizations of *K* factors (or *K+1* factors with K observed and 1 unobserved). The code will then save its estimated sensitivities. These sensitivities are needed to explain (in a later time) the monthly portfolio excess returns of the first month which follows the rm months (in our case January 2005). In sequence, the code will roll forward one month in the sample and run the same regression for the first rm realizations (in our case the period between February 2000 and January 2005). These estimates will then be saved as they are needed (in a later time) to explain monthly portfolio excess returns for the following month (in our case February 2005). The same procedure will be repeated until the last regression provide the estimated sensitivities which will further be used to explain monthly excess returns of the last month in the sample (i.e. December 2017). All this procedure described above will be repeated for all portfolios. Up to this point, the algorithm has constructed a matrix with the name **PANELM** and the user can proceed to the panel data analysis, as described in subsection (6.5).

Output data

There are three output arguments in this code:

1. **PANELY**: Is a matrix of size [*(T-rm)xP*] x [*K+3*] (or [*(T-rm)xP*] x [*K+4*] if the user has decided to include the residual market risk in the model). The first column of this matrix denotes the month in the sample. Since we have used the first rm observations to derive beta estimates for the calendar year which follows the rm month, the first scalar of this column is 1 and represents the first calendar year within the testing period. In our sample, 13 calendar years constitute the entire testing period (2005- 2017), thus 13 observations have been added for every portfolio. The second column denotes the number of portfolio (i.e. 1 is referred to the first portfolio, 2 to the second, and so on). The third column displays the annual portfolio excess returns depending on the month and the portfolio of columns 1 and 2 respectively. All of the following columns present the beta coefficients as have been estimated by the time-series regressions. Bear in mind that the arrangement of the factors is exactly the same as the user has specified in **FACTORS** of input arguments. Therefore, the fourth column contains the factor sensitivities (betas) associated with the 1st factor of **FACTORS**, for all portfolios and testing months, the fifth column contains the betas associated with the 2nd factor of **FACTORS**, etc. The last column always contains the residual market risk (unobserved factor) in case the user has set: **unobs**={1} in the input arguments. To sum up, the user will obtain a matrix with the following values:
   [Year; Portfolio; Excess Returns; Betas{Factor1};…;Betas{FactorK};Betas{Unobserved Factor}]
   Scrolling down to this matrix the user will observe the values of all portfolios (in our case 1 through 30) for all years in the testing period (in our case 1 (2005) through 13 (2017)).

2. **PANELM**: Is a matrix of size [*(T-rm)xP*] x [*K+3*] (or [*(T-rm)xP*] x [*K+4*] if the user has decided to include the residual market risk in the model). The first column of this matrix denotes the month in the sample. Since we have used the first rm observations to derive beta estimates for the first month which follows the rm months, the first scalar of this

column must have the value rm+1 (in our case 61, indicating this row is referred to the 61th month of our sample, that is January 2005). The second column denotes the number of portfolio (i.e. 1 is referred to the first portfolio, 2 to the second, and so on). The third column displays the monthly portfolio excess returns depending on the month and the portfolio of columns 1 and 2 respectively. All of the following columns present the beta coefficients as have been estimated by the time-series regressions. The user will obtain a matrix with the following values:

[Month; Portfolio; Excess Returns; Betas{Factor1};…;Betas{FactorK};Betas{Unobserved Factor}]

Scrolling down to this matrix the user will observe the values of all portfolios (in our case 1 through 30) for all months in the testing period (in our case 61 (January 2005) through 216 (December 2017)).

3. **UNOBSFACTOR**: Is a column vector of the residual market risk realizations for the entire sample period (in our case January 2000 through December 2017), and not the testing period of *T-rm* observations.

B.2 The code

```
function [PANELY,PANELM,UNOBSFACTOR] =
taipfirstpass(PORTFOLIOS,FACTORS,INDEXRET,BREAKS,Rf,rm,unobs)
%This code was constructed by Symeon Taipliadis as a part of his thesis.
%Last update: 02.08.19. New updates may exist.
%For related questions please contact to s.taipliadis@gmail.com
%As a guide see Appendix B and subsection 5.4.
%set unobs={1} to include the residual market risk OR ={0} if not included.
%User can set exogenously structural breaks for the Unobserved factor.
%rm: the number of months is taken into account to estimate each beta.
%Size of Matrices: PORTFOLIOS(T,P),FACTORS(T,K),INDEXRET(T,1).
%PANELY: Extracts in panel form a matrix with columns:
% [Year |No of Portfolio(1:P)|Portfolio Annual Returns(rm:T)|Beta Coeffs of K
%Observed factors (and 1 Unobserved factor)]
%PANELM: Extracts in panel form, a matrix with columns:
% [No of month(rm:T)|No of Portfolio(1:P)|Portfolio Monthly
%Returns(rm:T)|Beta Coeffs of K Observed factors (and 1 Unobserved factor)]
%%
%IDENTIFICATION OF RESIDUAL MARKET FACTOR.
tb=length(BREAKS(:)); %Number of structural breaks.
if tb==1 && BREAKS(1)==0
    tb=0; %In this case there are no structural breaks at all.
end
[T,P]=size(PORTFOLIOS);
K=length(FACTORS(1,:)); %Number of Observable factors.
X=[ones(T,1) FACTORS];
UNOBSFACTOR=zeros(T,1);
strpt=0;
endpt=0;
for t=1:tb+1
    if t<=tb
    strpt=endpt+1;
```

```
    endpt=BREAKS(t)-1;
    elseif t>tb
    strpt=endpt+1;
    endpt=T;
    end
B=X(strpt:endpt,:)\INDEXRET(strpt:endpt,1); %size:(K+1,1);
INDEXREThat=X(strpt:endpt,:)*B; %size:(T,1);
UNOBSFACTOR(strpt:endpt,1)=INDEXRET(strpt:endpt,1)-INDEXREThat;
end
%%
%1st PASS (TIME-SERIES) REGRESSIONS TO IDENTIFY BETA COEFFICIENTS.
%Code starts with the case where:
%Beta coefficients change per month. (in thesis: Alternative methodology).
if unobs==0
REGRESSORS=[ones(T,1) FACTORS];
BETAS=zeros(T-rm,K+1,P);
for p=1:P
    for t=1:(T-rm)
        z=t+rm-1;
        BETAS(t,:,p)=(REGRESSORS(t:z,:)\(PORTFOLIOS(t:z,p)-Rf(t:z,1)))';
    end
end
PANELM=zeros((T-rm)*P,K+3);
z=0;
for p=1:P
   for t=1:(T-rm)
        PANELM(z+t,1)=rm+t;
        PANELM(z+t,2)=p;
        PANELM(z+t,3)=PORTFOLIOS(rm+t,p)-Rf(rm+t);
        PANELM(z+t,4:K+3)=BETAS(t,2:K+1,p);
   end
    z=z+(T-rm);
end
elseif unobs==1
REGRESSORS=[ones(T,1) FACTORS UNOBSFACTOR];
BETAS=zeros(T-rm,K+2,P);
for p=1:P
    for t=1:(T-rm)
        z=t+rm-1;
        BETAS(t,:,p)=(REGRESSORS(t:z,:)\(PORTFOLIOS(t:z,p)-Rf(t:z,1)))';
    end
end
PANELM=zeros((T-rm)*P,K+4);
z=0;
for p=1:P
   for t=1:(T-rm)
        PANELM(z+t,1)=rm+t;
        PANELM(z+t,2)=p;
        PANELM(z+t,3)=PORTFOLIOS(rm+t,p)-Rf(rm+t);
        PANELM(z+t,4:K+4)=BETAS(t,2:K+2,p);
   end
    z=z+(T-rm);
end
else
disp('ERROR: unobs takes the values 0 and 1. 0: Do not take into account the 
residual market risk. 1: Take into account the residual market risk')
end
```

```
%%
%Use annualized excess returns to derive the risk premia.
%Beta coefficients change per annum. (in thesis: Main methodology).
if unobs==0
PANELY=zeros(((T-rm)/12)*P,K+3);
Y=(T-rm)/12;
j=0;
for p=1:P
    st=rm;
    en=st+11;
    i=1;
    for y=1:Y
        PANELY(y+j,1)=y;
        PANELY(y+j,2)=p;
        PANELY(y+j,3)=sum(PORTFOLIOS(st+1:en+1,p))-sum(Rf(st+1:en+1));
        PANELY(y+j,4:K+3)=BETAS(i,2:K+1,p);
        st=st+12;
        en=st+11;
        i=i+12;
    end
    j=j+Y;
end
elseif unobs==1
    PANELY=zeros(((T-rm)/12)*P,K+4);
Y=(T-rm)/12;
j=0;
for p=1:P
    st=rm;
    en=st+11;
    i=1;
    for y=1:Y
        PANELY(y+j,1)=y;
        PANELY(y+j,2)=p;
        PANELY(y+j,3)=sum(PORTFOLIOS(st+1:en+1,p))-sum(Rf(st+1:en+1));
        PANELY(y+j,4:K+4)=BETAS(i,2:K+2,p);
        st=st+12;
        en=st+11;
        i=i+12;
    end
    j=j+Y;
end
end
```

Appendix C

Table C.1

This table confirms that the condition of mean zero variables holds for all candidate factors over the entire sample period [Jan. 2000 – Dec. 2017]. Series of *UIP*, *UINF*, *UDP*, *ΔTERM*, *UEPU* and *UTG* have been derived from equations presented in subsection 5.3. Series of Θ_{EPU} and η_{TG} have been derived from equations presented in subsection 6.4.

	UIP	UINF	UDP	ΔTERM	UEPU	UTG	Θ_{EPU}	η_{TG}
Sample Size	216							
Sample Mean	-2.54E-05	2.43E-06	-1.17E-06	-5.09E-06	3.29E-05	1.63E-05	-5.40E-18	4.37E-19
Standard Deviation	0.005932	0.002609	0.002075	0.003046	0.166108	0.00249	0.156519	0.001642
Null Hypothesis	Zero mean value							
Test Statistic (d.f. 215)	-0.06304	0.013679	-0.00826	-0.02457	0.00291	0.096379	-5.07E-16	3.91E-15
Two-tailed P-Value	0.9498	0.9891	0.9934	0.9804	0.9977	0.9233	1	1

Table C.2

The following table provides the Partial Autocorrelation Function (PACF) for the first 14 lags (months) of the two variables introduced in subsection 6.4. These are, restricted shocks of policy uncertainty (Θ_{EPU}) and restricted shocks of technology developments (η_{TG}) (see equations 6.4.1 and 6.4.2 respectively). One star (*) indicates significance at the 10% level. Box-Pierce Q-statistic is also provided along with its p-value for the first 14 lags. Under the null hypothesis of Box-Pierce Q test, series are serially uncorrelated. Based on our sample we could not reject the null hypothesis for both series.

Variable	**PACF**							
	1M	**2M**	**3M**	**4M**	**5M**	**6M**	**7M**	**8M**
η_{TG}	-0.0238	-0.0111	-0.0097	-0.0359	-0.0004	0.0623	-0.0956	0.0385
Θ_{EPU}	-0.0312	-0.0349	-0.0054	-0.0693	-0.0339	-0.1242 *	-0.0722	-0.1135 *

Variable	**PACF**						**Box-Pierce**	
	9M	**10M**	**11M**	**12M**	**13M**	**14M**	**Q-stat.**	**P-value**
η_{TG}	0.0513	-0.0713	-0.0952	-0.0409	0.0884	0.0514	10.0953	0.755
Θ_{EPU}	0.0032	0.0161	-0.0018	-0.0024	-0.0146	-0.0703	8.6046	0.856

Table C.3

This table depicts the Correlation Matrix of table 5.6 (Panel A) when series of policy uncertainty related factor (*UEPU*) and technology developments factor (*UTG*) are substituted by their restricted series (Θ_{EPU} and η_{TG} respectively). Restricted shocks on these factors have been presented in subsection 6.4.

	UIP	UINF	UDP	ΔTERM	Θ_{EPU}	η_{TG}
UIP	1	0.0243	-0.1636	-0.2338	0.0877	0.0000
UINF		1	-0.1176	0.1356	0.0454	0.0000
UDP			1	-0.1804	0.0000	0.0000
ΔTERM				1	0.0000	0.0000
Θ_{EPU}					1	0.0849
η_{TG}						1

Figure C.1 – Series related to Industrial Production

The first graph depicts series of monthly growth rates of industrial production (*PROD*). The second graph shows the estimated series of unanticipated growth of industrial production (*UIP*).

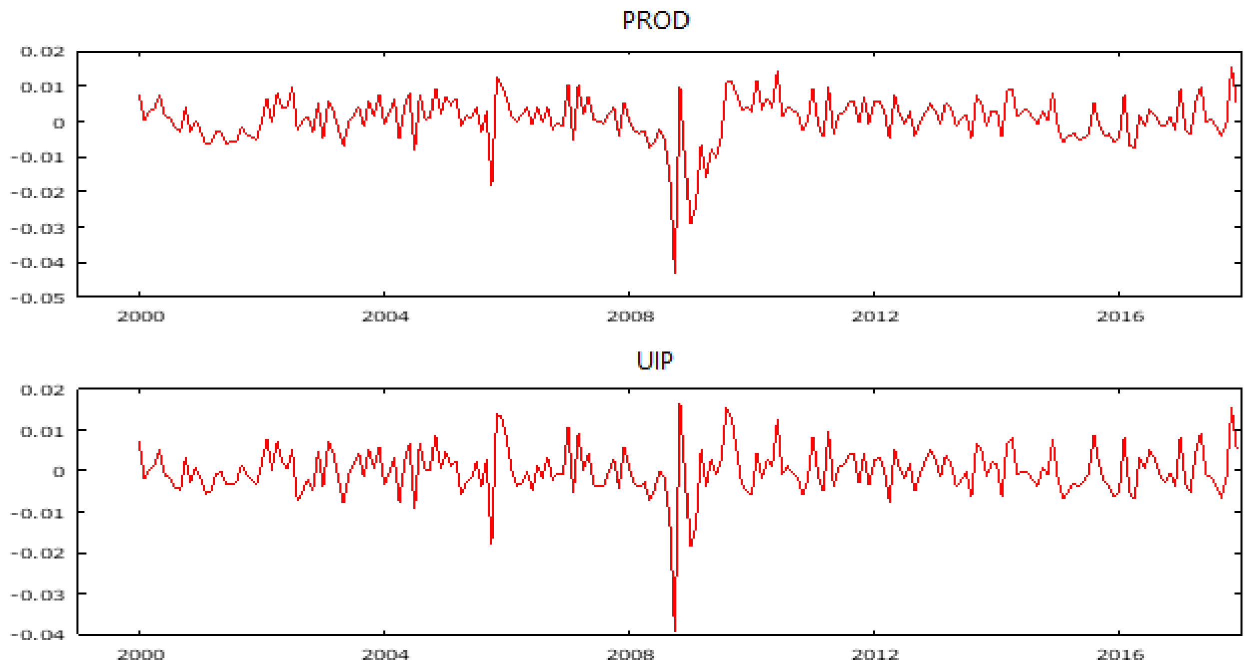


Figure C.2 - Series related to Inflation

The first graph depicts monthly series of inflation (*INF*). The second graph shows the estimated series of unanticipated inflation (*UINF*).

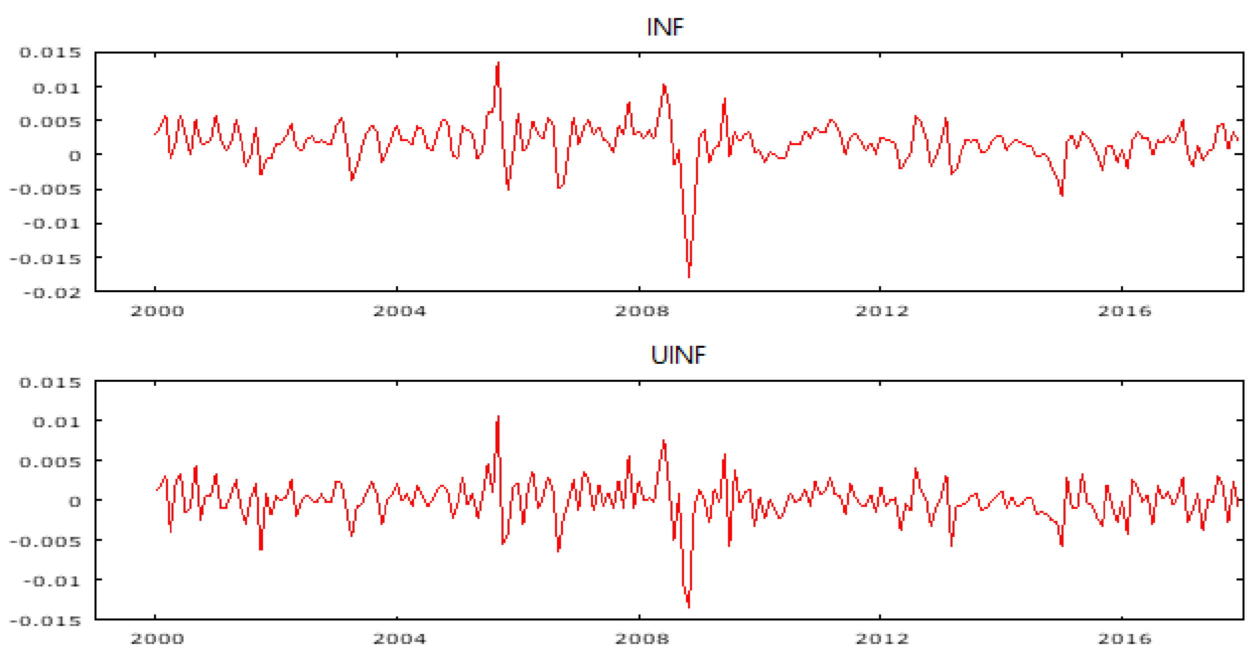


Figure C.3 - Series related to Default Premium

The first graph depicts the series of monthly movements of default premium (*ΔDEF*). The second graph shows the estimated series of unanticipated movements of this premium (*UDP*). Default Premium is measured as the spread between Moody's Baa Corporate bond yield minus 10 Year Treasury (Constant maturity) yield.

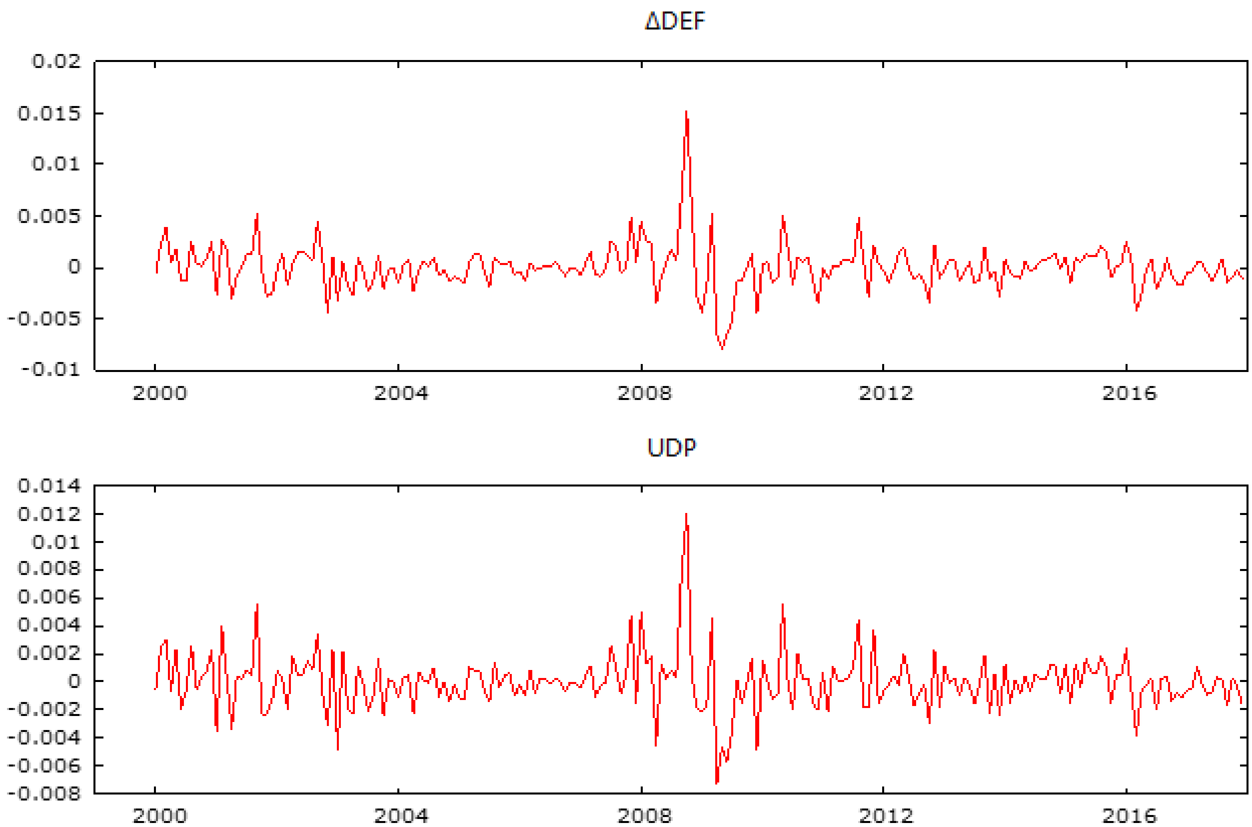


Figure C.4 - Series of Term Structure

The following graph depicts series of the shifts in the slope of the yield curve (*ΔTERM*) measured as monthly changes of the spread between the 10 Year minus 3 Month Treasury yields.

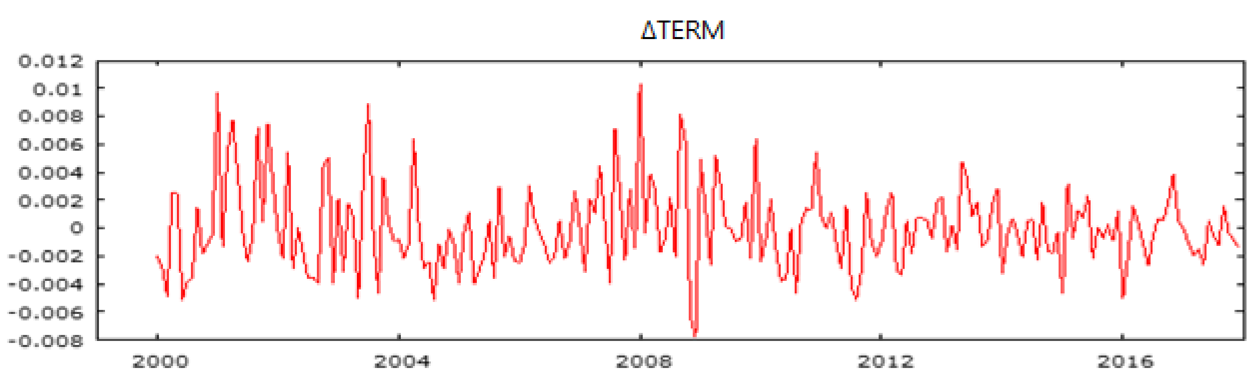


Figure C.5 - Series related to Policy Uncertainty

The following three line-graphs are related to policy uncertainty. The first graph (*EPUG*) depicts series of (%) monthly changes of EPU index of Baker, Bloom and Davis (2016). The second graph (*UEPU*) represents the unanticipated portion of the first series and the third graph is the series which captures the restricted shocks (Θ_{EPU}) as derived from the residuals of equation (6.4.1).

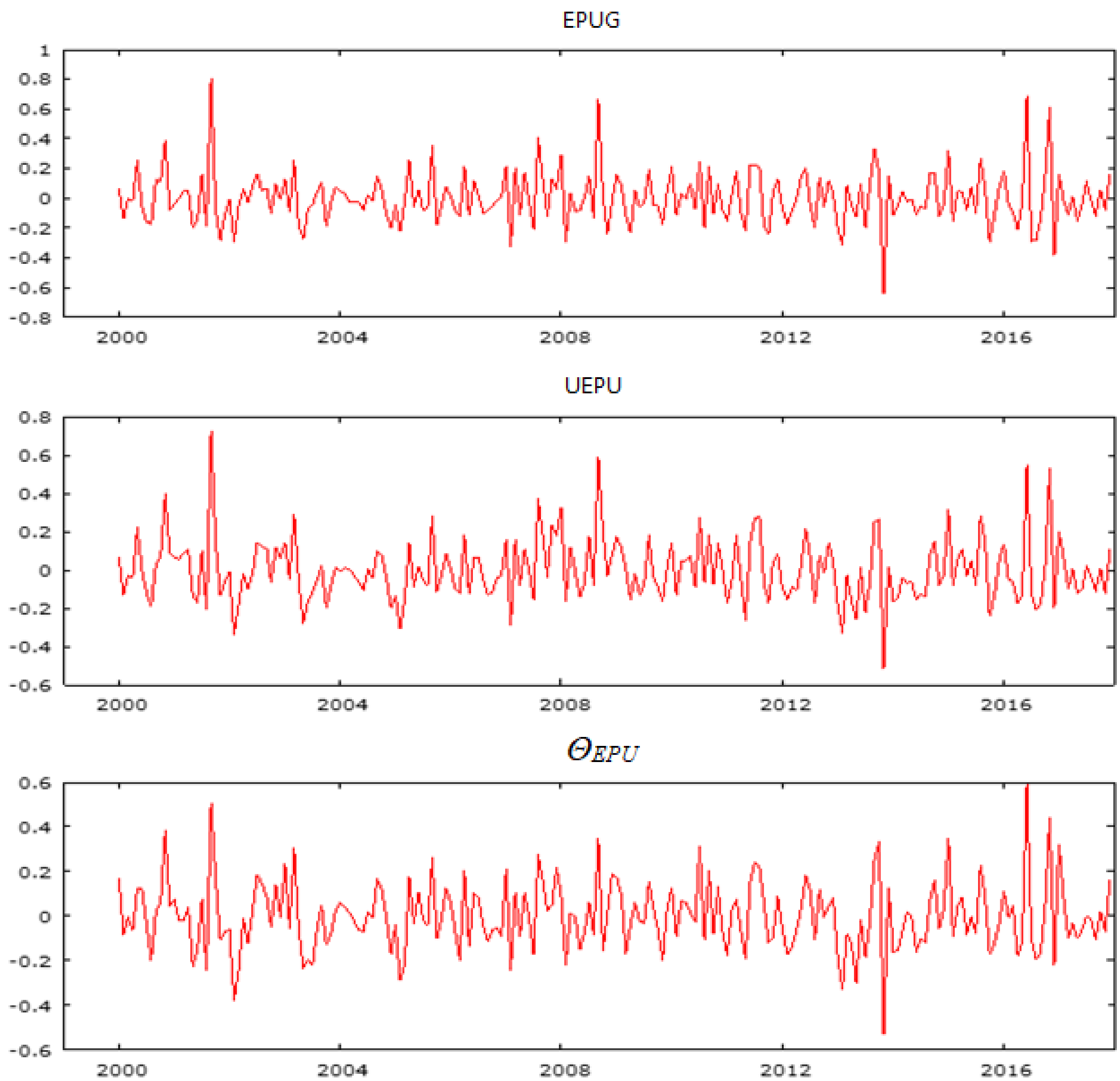
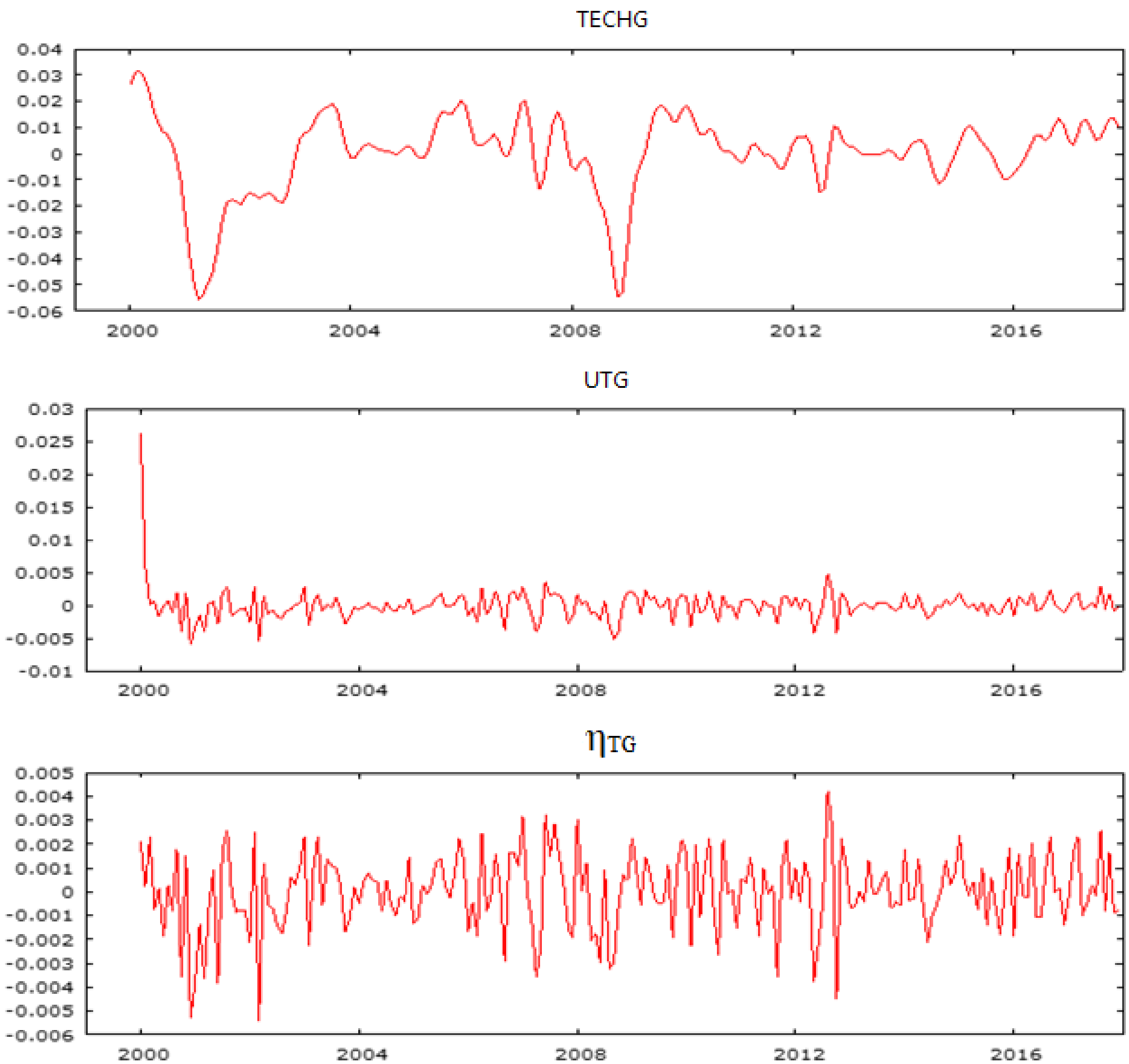


Figure C.6 - Series related to Technology Growth

The first graph (*TECHG*) represents the series of (%) monthly changes of San Francisco Tech-Pulse index. The second graph (*UTG*) represents the unanticipated portion of the first series and the third graph (η_{TG}) is the series which captures the restricted shocks as derived from the residuals of equation (6.4.2).



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