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# THE RELATIONSHIP BETWEEN INNOVATION AND STOCK RETURNS


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# The relationship between innovation and stock returns

## *Does innovation explain stock market returns?*

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## *Abstract*

This paper contributes to the debate which (risk) factors can explain stock returns. In this paper a new factor is added to the Fama French three-factor model, namely the factor innovation. Based upon analysis for the years 1993 - 2010, I find that (1) innovation can explain stock returns, and (2) the relevance of the size factor diminishes when we introduce the innovation factor, but the relevance of the value factor increases. The relationship between stock returns and innovation is positive using raw patent counts as proxy for innovation, but negative using the percentage change in patents as proxy. The positive relation suggests that stocks with a lot of patent counts yields abnormal return in comparison to stocks with low patent counts. It could be that more patents results in more intangibles relative to total assets. This could lead to more risky firms, because the value of intangibles are hard to value. So, it increases the risk premium and has a positive effect on stock returns. However, the coefficient of the factor innovation based on percentage change in patent counts is negative. The explanation could be that it alerts competitors of progress,. It is rather surprising that the beta of the factor innovation based on percentage change in patent counts is negative and that the beta of the factor innovation based on raw patent counts is positive. It could be that high quality patents (measured by percentage change in patent counts) are treated differently. The argument that the patent alerts competitors of progress could become more relevant for high quality patents.  Adding a new factor to the Fama French three-factor model is useful when it captures the fluctuation of the excess return between the different portfolios, which cannot be captured by the other three factors. I did not find a pattern between the excess return and the beta of the innovation factor, It seems that a major part of the fluctuation in excess return is already captured by the Fama French three-factor model.


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## I. INTRODUCTION

There are many ups and downs in the financial markets, especially during the recent crisis. Additionally, the magnitude of the ups and downs fluctuates. Most of the people do not understand these fluctuations in stock prices anymore, and the question can be asked : 'What exactly influences stock returns and the magnitude of stock returns?'.

Models are developed to create insight in the relationship between risk and return. One of the most famous models is the Capital Asset Pricing Model (CAPM). Fama and French (1992) conclude that this model is not that useful in the real world and they developed a new model, namely the Fama French three-factor model. In this model two factors, the size factor and value factor, are added to the single factor in the CAPM. It is nowadays well-accepted that other variables than the market premium are related to average returns. However, the theoretical background of the size and value factor is still weak. Some researchers (such as Liew and Vassalou, 2000 and Banz, 1981) found evidence that the factors are proxies for risks. However, other empirical papers (such as Lakonishok, Shleifer and Vishny, 1994 and Chan, Karceski and Lakonishok, 2000) show that the factors could also be a proxy of irrational behavior.

Also other factors are found that can explain stock returns, such as the momentum effect. In this paper I investigate the relationship between stock returns and innovation. Innovation is one of the most important factors in the growth of new products, sustaining incumbents, creating new markets, transforming industries, and promoting the global competitiveness of nations. Some claim to invest more in R&D to increase the competitive edge and leadership. Innovation is also one of the main goals for governments to stimulate economic growth. As stated by Peilei Fan (2011) the GDP growth in India and China during the period 1981 till 2004 can be explained by innovation capacity. To strengthen their innovation capacity they invest in R&D and personnel, patents, and high-tech/service exports. Hence, innovation is mentioned as one of the main drivers for economic growth. The main research question is: *Does innovation explain stock market returns?*

In this paper I use patents as proxy for innovation. According to Sood and Tellis (2009) the development stage of a new product (i.e., innovation) yields the highest return. Patents are very important in the development stage. Hence, patents should be a good proxy for innovation. However, raw patent counts need to be quality adjusted according to Hall, Jaffe, and Trajtenberg (2005). Normally, citation-weighted patents are used to overcome this problem. However, this information is not publicly available. Alternatively, I used percentage change in patent counts. When patents rise relative to the previous year it could be that the patents in the previous year were developed into economically feasible successful innovations resulting in more patents the next year (Trajtenberg, 1990). So, the frequency is assumed to be positively correlated with technological importance.

To obtain more understandable results and conclusions I constructed ten portfolios. Fama and French (1993) also created portfolios to obtain more understandable results. The portfolios are formed based on patents. I will use two approaches to form the portfolios, namely (1) based on raw patent counts and (2) based on the percentage change in raw patent counts. For example, Austria has the highest percentage change in raw patent counts in 1993. Subsequently, Ireland and the Netherlands have the highest percentage change in raw patent counts in respectively 1994 and 1995. Austrian stocks in 1993, Irish stocks in 1994 and Dutch stocks in 1995 will be formed into one portfolio. This is also done for the countries with the lowest percentage change in raw patent counts and everything in between. Using the portfolios I calculated the factor innovation. The factor innovation is calculated in two ways for each approach, namely using (1) the highest en lowest three countries and using (2) the highest and lowest five countries. For example, (1) the average return on stocks with the 30% highest raw patent counts minus the average return on stocks with the 30% lowest raw patent counts and (2) the average return on stocks with the 50% highest raw patent counts minus the average return on stocks with the 50% lowest raw patent counts. So, in 1993, the average return of the lowest three portfolios (or the average return in three lowest countries) based on percentage change in raw patent counts is subtracted from the average return of the highest three portfolios (or the average return in three highest countries) based on percentage change in raw patent counts. Fama and French (1993) constructed the factor size and value, in a similar way.

Using a dataset from 1993 till 2010, I found that the factor innovation can explain stock returns. I found a positive coefficient of the factor innovation based on raw patent counts. However, using the factor innovation based on percentage change in patent counts, there is a negative relationship between innovation and stock returns. The positive beta suggests that stocks with a lot of patent counts yields abnormal returns in comparison to stocks with low patent counts. As stated by Sood and Tellis (2009) patents reduce the uncertainty about the payoffs in the future of the innovation. As said by  Sood and Tellis (2009), an explanation for the negative coefficient could be that it alerts competitors of progress. Using raw patent counts provides different results than using the percentage change in patent counts as proxy for innovation. It could be that high quality patents (measured by percentage change in patent counts) are treated differently. The argument that patent alerts competitors of progress and triggers imitators could become more relevant for high quality patents. Adding a new factor to the Fama French three-factor model is useful when it captures the fluctuation of the excess return between the different portfolios, which cannot be captured by the other three factors. It seems that a major part of the fluctuation in excess return is already captured by the Fama French three-factor model.

Furthermore, the paper focused on the following hypotheses: (1) the relevance of the size factor and the value factor diminishes when we introduce the innovation factor and (2) the results are not similar between different time periods. The relevance of the size factor diminished when we introduce the innovation factor, but the relevance of the value factor increases. Adding the innovation factor should decrease the predictive power of the size and value factor. Liew and Vassalou (2000) found a positive relation between the three factors and the GDP growth. They argue that this is evidence that the factors could be a proxy of business cycle risk. When we introduce the business cycle risk (and thus patents) the significance of the size and value factors should decrease and even become insignificant. The underlying assumption is that innovation is a proxy for business cycle risk. Finally, I found that the betas of the factor innovation does not vary a lot over time. The factor is more relevant during the boom and the run-up and not important during the aftermath.

Lev and Sougiannis (1999) show that the return premium due to R&D is higher in the good state than in the bad state of the world. Due to high correlation between R&D and patents, I would expect that the coefficient during the good state is higher than during the bad state of the world. This is not consistent with the results.

I would like to point out some limitations in this research. The first limitation is that there is no monthly data about patent counts, but only annually. Furthermore, data of patent counts are only available for the period 1993 till 2011. Additionally, patent counts are available at country level and not at firm level. Therefore, I did research at an international level and not country specific. The results will be more precise if I could use information at firm level. Individual stocks can be sorted into portfolios based on patents and this will improve the construction of the innovation factor. According to Griffin (2002) country-specific models are more accurate and explain more time-series variation than a world three-factor model. Finally, information about citation weighted patents are not publically available.

The remainder of this paper is organized into six chapters. In chapter two I give a literature overview about the different asset pricing models. Chapter three contains literature regarding innovation. Chapter four described the data and the methodology. Chapter five focuses on the empirical results and their interpretations. The last chapter, namely chapter six, summarizes the key results.

## II. Relationship between risk and return

With a model that gives a relationship between risk and return it is possible to provide a benchmark rate of return for evaluating possible investments. So we can analyze whether the expected return that is forecasted is more or less its fair return given its risk. Furthermore, such a model will be useful to make an educated guess about the return on an asset. In this chapter two types of these models are described. I will investigate whether adding an innovation factor increases the predictive power of the model. With this research I hope to give more insight in the relationship between risk and return of stocks.

### A. Capital Asset Pricing Model

Using the fundaments of Markowitz and making important assumptions, discussed in the next paragraph, Sharpe (1964), Lintner (1965) and Black (1972) developed a framework to determine how the risk of an investment affect its expected return.

In order to understand the relationship between risk and return some simplifying assumptions are needed. In case of the Capital Asset Pricing Model the main assumptions are: (1) homogeneous expectations (about the future in terms of means, variances and covariance), (2) the capital market is in equilibrium, (3) investors can lend and borrow unlimited amounts at a risk-free interest rate, (4) all investors hold efficient frontier portfolios, (5) no transaction costs and no taxes, and (6) investors are rational, risk-averse and price takers. Additionally, the model assumes that standard deviation of past returns is a perfect proxy for the future risk. The implications of the main assumptions are that every investor invests in the riskless asset and in the market portfolio. Furthermore, all the investors hold the risky assets in the same proportions and the tangent portfolio is the market portfolio.

A distinction can be made between different types of risks. The total risk of an individual stock can be separated into systematic risk (i.e. market risk) and idiosyncratic risk (i.e. diversifiable, unique or unsystematic risk). The unsystematic risk can be eliminated by diversification. The individual risk of securities can be diversified away, but the contribution to the total risk caused by the covariance terms cannot be diversified away. The volatility can be effectively reduced without significant cost by diversifying and therefore the investors should not be compensated for that portion of volatility which is firm specific and has no impact on a well diversified portfolio. According to the CAPM the cross-sectional variation of expected stock returns can only be explained by one systematic risk factor, namely the market. The relation between risk and return according the well-known Sharpe-Lintner CAPM, is as follows:

$$\boldsymbol{E(R_i) = R_f + \beta_i \left(E(R_M) - R_f\right)} \qquad \textit{(2.1)}$$

This linear equation is called the Security Market Line (SML) and it relates the return of individual securities and portfolio of securities with their exposure to the market. The CAPM is an explanation of the cross-sectional variation of securities returns. Furthermore, it says that there is a linear relation between expected return and beta. This implies that differences in returns of securities can only be due to differences in the exposure of these securities to the market (i.e. that the securities have different covariance with the market portfolio). Hence, the only risk priced is the systematic risk and the idiosyncratic risk is diversified away without affecting the return and therefore it is not priced. The variance of a security can be composed by a systematic part ($\beta_i^2\ \sigma_m^2$) and an unsystematic part ($\sigma_\varepsilon^2$) or in equation:

$$\boldsymbol{\sigma_i^2 = \beta_i^2\ \sigma_m^2 + \sigma_\varepsilon^2} \qquad \textit{(2.2)}$$

Jensen (1968) argues that the model also implies a time series regression test. The expected excess return of a security ($R_{it} - R_{ft}$), is according to the Sharpe-Lintner theory equal to the exposure ($\beta_i$) to the expected CAPM market premium$\left(R_{Mt} - R_{ft}\right)$. Jensen's alpha measures the abnormal return or pricing error above and beyond the rate of return expected by the CAPM. Hence, the expectation is that alpha is equal to zero. If alpha is positive the security is underpriced and the price should rise and vice versa if alpha is negative. Empirical work[1] shows that the intercept is not zero, but negative for securities with high betas and positive with low betas. Mostly, the alpha is significantly positive but small. In addition the exposure to the market is lower than expected. The intercept should be equal to the risk free rate and the slope should be equal to the market premium. These findings result in a too flat Security Market Line. According to the CAPM the observations should be along the line. This was the case in the years 1931 till 1965. The relative flat slope could be explained because assumption 3 is violated. Hence, there are restrictions about borrowing and lending at the risk free rate. Black (1972) developed a version of the CAPM without risk-free borrowing or lending. Still, the long-run average returns are significantly related to beta (Black, 1993). Assuming that the used market proxy is a good proxy for the real market portfolio the Sharpe-Lintner has limitations in explaining the risk and return relationship in the real world. There are factors found other than beta which seem important in pricing securities, also known as anomalies (Fama and French, 1992).

Fama and French (2004) conclude that there are securities that have a high beta and with a lower return than securities that have a low beta. CAPM is an equilibrium relationship and according to the model stocks that have a high beta are expected to give a higher return than low beta stocks, because these stocks are more risky. Hence, the model contradicts the real world. Furthermore, it does not mean that stocks with a relative high beta will give a higher return over all intervals over time. Otherwise it will be less risky. Additionally, most of the individuals and institutions hold portfolios that are not similar as market portfolio. Finally, the assumptions underlying the CAPM have as consequence that it is very difficult to investigate certain (real life) influences. Due to all this critique about the CAPM the question could be asked whether it is even relevant that the model does not hold in the real world in all scenarios.

For valuing investment opportunities (including companies) practitioners could use the discounted cash flow (DCF) method. In this model the present value of the investment is determined by discounting the future free cash flows. Hence, the model depends on the forecast of its free cash flows and the appropriate discount rate. The outcome is highly sensitive to both of these parameters. The discount rate is according the CAPM determined by its risk-free rate, the market risk premium and its beta. Incorrect or inaccurate estimation of the discount rate results in a wrong net present

[1] Fama and French (2004)

value, which has a major effect on the decisions of companies. Hence, it is important that the model also hold in the real world in most cases. Although the model does not withstand all the empirical tests, it is useful to create insight in the relationship between risk and return.

### B. Arbitrage Pricing Theory

The CAPM is a single factor model with the market premium to describe aggregate risk. With the help of multiple factor linear models more (risk) factors are added, which could result in a more descriptive and predictive model. Ross (1976) constructed a more general model to explain the cross section of securities returns. Asset prices tend to move together and the factor model captures this fact. With the help of linear factor models it assumes that one or more random factors influences the returns and explain all the co movement (i.e. all systematic risk). Due to the fact that the APT is a general model we need to find factors to implement the APT. The literature uses three strategies, namely (1) using macroeconomic variables, (2) using statistical analysis and (3) data mining. The latter has been used by Eugene Fama and Kenneth French for their three-factor model.

### C. Fama and French three-factor model

Fama and French (1996) introduce their three-factor model: (1) the excess return on a broad market portfolio, (2) the difference between the return on a portfolio of small stocks and the return on a portfolio of large stock, and (3) the difference between the return on a portfolio of high book-to-market stocks and the return on a portfolio of low book-to-market stocks or in equation:

$$E(R_{it}) = R_{ft} + \beta_{iM}\left(E(R_{Mt}) - R_{ft}\right) + \beta_{is}E(SMB_t) + \beta_{ih}E(HML_t) \qquad (2.3)$$

This model partly rescued the capital asset pricing model, because the first factor is the same in both models. However, Fama and French (1992) found that beta fully loses its predictive power in a regression that includes the book-to-market ratio and size as factors. The three-factor model explains the expected return from three sources of risk according to Fama and French. The two extra factors in comparison with the CAPM could be proxies for the true sources of risk, which are unknown for us. The theoretical motivation is still relatively weak. In the next paragraphs the additional factors are described. The two factors became very popular among researches the recent years, resulting in various findings which will also be discussed in the next paragraphs.

#### *Size effect*

The size effect means that smaller firms appear to earn higher expected returns than larger firms. It is calculated as the average return for the smallest 30% of stocks minus the average return for the largest 30% of stocks in that month. A positive SMB[2] means that the small cap stocks outperformed the large cap stocks in that specific month and vice versa for a negative SMB.

Recent empirical studies[3] found that the size effect has disappeared since the early 1980s. This suggest that the size effect is "dead", however due to lack of theory behind the model there is an

[2] Small minus Big

[3] van Dijk (2011)

emergence of several theoretical models[4] in which the size effect becomes endogenously as a result of systematic risk. According to van Dijk (2011) the conclusion that the size effect lost its explanatory power is premature. He shows that the size effect in the U.S. has been large and positive over the years.

*Empirical evidence*[5]

Banz (1981) found a positive size premium of 0.40% in the period 1936 - 1975 in the U.S. market. Over the period 1963 and 1977 this results holds according to Reinganum (1981) with a higher size premium of 1.77% per month. The findings of Reinganum are revised by Brown, Kleidon, and Marsh (1983) using average daily returns and logarithm of the market capitalization and showed a size premium of 1.85%. Using a broader sample the size premium is 2.5% as stated by Keim (1983). He also note that the size factor cannot explain everything of the variation in return. Finally, Lamoureux and Sanger (1989) conclude that the size premium ranged from 1.7% to 2.0% for the period between 1973 and 1985. Of course Fama and French (1992) also showed a significant size effect and they found a size premium of 0.63% per month.

Fama and MacBeth (1973) researched the relationship between market value and returns and found a negative and significant relation. One reason could be that small stocks are not preferred by investors due to insufficient information, resulting in higher returns (Banz). In line with this Merton (1987) developed the investor recognition hypothesis.

According to van Dijk (2011) almost all results in the international market show a positive significant relationship between size and return. Only in Korea there is a negative relationship and for the Netherlands there is only found a positive insignificant relationship by Doeswijk (1997). The evidence in the international market gives us a relatively consistent result. In most countries small cap stocks yield higher return than big cap stocks. According to van Dijk (2011), the size premium is in most cases between 0.4% and 1.2% per month. These findings suggest that the concerns regarding data mining are not important[6]. However, as stated by van Dijk (2011) the results have some pitfalls, namely (1) the sample composition in these results are not very reliable, because the small amount of data points, relative few portfolios, (2) it is very difficult to find evidence that small cap stocks also outperform big cap stocks on a risk-adjusted basis, (3) the method used to measure size, because using the size of a firm relative to the average of firms in that specific country has as consequence that size becomes insignificant as reported in Annaert, Van Holle, Crombez and Spinel (2002)[7], and (4) most studies do not perform robustness checks.

Rouwenhorst (1999) concludes that the size premium is positive for only 12 of the 20 countries in his dataset. Heston, Rouwenhorst, and Wessels (1999) found that the significance of the size effect in

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[4] Based on investor behavior, firm-level investment decisions, and stock market liquidity.

[5] Van Dijk (2011)

[6] More information about data mining concern can be found in the critique section of this chapter.

[7] According to Ken French this method reduce the variation in the size factor, resulting in lower statistical power.

those 12 countries is mostly a result of variation within countries. Also Barry, Goldreyer, Lockwood, and Rodriguez (2001) report a significant size effect when size is measured relative to the local market. Note that differences in the magnitude of the size effect between the findings of different countries can be explained by market characteristics[8].

*Explanations for the size effect*

There are different explanations for the size effect, namely it is (1) a proxy for the exposure of a stock to risk, (2) a proxy for (irrational) investor behavior, (3) a proxy for the transaction costs and liquidity risk, and (4) it could be that the factor is just statistical luck.

Banz (1981) conclude that the size does not have to be responsible for the effect, because it could be just a proxy for one or more true unknown factors. This is in line with the way Fama and French (1993) interpret the variables. The true source of risk behind the size effect could be that small firms should be expected to be more sensitive to many risk factors, because they are less diversified and therefore more vulnerable to negative financial events. Introducing time variation (or cyclical behaviour) in betas results in insignificancy of the factor SMB and thus is not important anymore[9]. Hence, size could be a proxy of *business cycle risk*. This is in line with the findings of Liew and Vassalou (2000). They found a positive relation between the three factors and the GDP growth. Fama and French (1995, 1996) suggest that one of the factors is related to *default risk*. In line with this suggestion Chan, Chen and Hsieh (1985) and Vassalou and Xing (2004) report that default risk is correlated with the size effect. Chan and Chen (1991) suggest that small cap stocks are usually "fallen angels" that have lost market value due to bad performance. In a recent paper Campbell, Hilscher and Szilagyi (2008) found that companies with high probability of default also have a high correlation with the size factor. However, they also found that these firms do not earn higher returns. This is not in line with the theory that the size effect is a proxy for default risk. Another risk could be the *idiosyncratic risk*. This type of risk is related to stock returns as shown in the paper of Goyal and Santa-Clara (2003). According to Makiel and Xu (2004) a proxy of idiosyncratic risk makes the size effect irrelevant. This finding suggests that the size factor is closely related to idiosyncratic risk. Berk (1995) argues that the size factor picks up any omitted risk factor. If the three-factor model does not hold in the real world, then this factor will be negatively linked with the return that is not explained by the model. A firm with riskier cash flow than another firm, but have the same size, will have a lower market value en thus a higher expected return.

An alternative explanation could be that it is a proxy for investor behavior. Chan and Chen (1991) found that smaller firms have performed badly in comparison with larger firms. If investors extrapolate this bad performance the stock price will be too low. When the *overreaction* is corrected the returns are higher. This is consistent with Chan, Karceski and Lakonishok (2000). Another explanation could be that the information about small firms is less well-known and less complete. *Incomplete information and the know-how about firms* could be the explanation of the size

[8] For example the trading mechanism, the type of investors, and market efficiency in general.

[9] Santos and Veronesi (2006) using labor income as the main state variable.

premium. This is consistent with Merton (1987) who found that less established firms show higher returns. Hou and Moskowitz (2005) also found this result, using a different method. Finally, it could be that investors like large stocks and dislike small stocks. Gompers and Metrick (2001) and Lakonishok, Shleifer and Vishny (1992) found evidence for this statement. Investments in small stocks are in the most cases difficult to defend to sponsors or other stakeholders.

Transaction costs and *liquidity* risk could be the explanation of the size effect. As said by Stoll and Whaley (1983) it is not possible to earn abnormal risk-adjusted returns on small stocks when taking the transactions costs into account. Nevertheless, the transaction costs cannot explain the size effect totally (Schultz, 1983). Different measures of liquidity such as bid-ask spread and turnover are related to stock returns. In line with Amihud (2002) the size effect is still significant even controlling for illiquidity. This suggests that illiquidity does not absorb the size effect completely. In this study they do not relate the size factor to liquidity (only illiquidity). This is also supported by Acharya and Pedersen (2005). Amihud also concludes that return of small firms depend for a major part on time-series variation in market liquidity. In other words, the changes in the size factor could be related to time-variation in the price of liquidity risk.

Various studies such as Amihud (2002) found that the size effect has disappeared since the early 1980s. Furthermore, Dimson and Marsh (1999) state that the size premium reversed in the U.K. over time. These two findings suggest that the size effect is "dead" and that it was just a *statistical luck*[10] that we found a factor which explained the stock returns rather well. However, there is not enough data to conclude that the size effect has disappeared, according to Van Dijk (2011). Furthermore, Pettengill, Sundaram and Mathur (1995) argue that there could be a difference between realized returns and expected returns over a long period of time[11]. Knez and Ready (1997) show that the size effect is driven by the 1% highest/smallest observations. Using a robust regression method[12] to trim the extreme return observations they show that the size effect is not significantly positive, but negative. The size factor seems to be due to a very small part of the small firms that do extraordinary well. They suggest that this is related to the '*turtle eggs' effect*, small cap stocks do not yield higher returns, but this is compensated by very few successful small size firms. Finally, the size effect can be explained for a substantial part by the abnormal returns of the small caps stocks in January. This is also known as the *January effect*. This effect can be explained by the window dressing hypothesis. Institutional investors have an incentive to buy stocks which performed well and sell stocks which performed badly. Another explanation of the January effect is the tax-loss selling hypothesis, meaning that the tax benefits create an incentive for investors to sell stocks at the end of the year that declined in price during that year. In the beginning of next year the selling pressure is diminished and therefore the prices rise. The latter explanation is more likely according to Van Dijk (2011).

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[10] More information in the critique section "data mining concerns".

[11] More information can be found in the Equity premium puzzle section.

[12] Least trimmed squares

Graham and Harvey (2001) found that the practice of corporate finance differs across the size of the firm. *The sophistication of corporate finance* could be an explanation of the size effect, but this is not yet empirical tested.

### *VALUE EFFECT*

This last factor is computed in the same way as the SMB factor, however Fama and French use the 50% largest and the 50% smallest book-to-market ratio and instead of the 30% used in the calculation of SMB. A positive HML[13] indicates that value stocks outperformed growth stocks in that month and vice versa if the factor is negative.

#### *Empirical evidence*

Fama and French (1992) found that value stocks earn abnormal return in comparison with growth stocks in the U.S. during the period from 1963 till 1991. According to Davis (1994) there is a value effect in the period before 1963 in the U.S. The value premium is also found in different market than the U.S. stock market. Value stocks in Japan also perform better than growth stocks according to Chan, Hamao, and Lakonishok (1991). This is consistent with the findings of Daniel, Titman, and Wei (2001) over the period 1975 till 1997. They further found that the value effect is significantly stronger in Japan than in the U.S. As stated by Capaul, Rowley and Sharpe (1993) the value effect is persistent in different markets. They show that there is a value effect for all the countries in their dataset[14] over the period 1981-1992.

#### *Explanations for the value effect*

There are different explanations for the size effect, namely it is (1) a proxy for the exposure of a stock to risk, (2) a proxy for (irrational) investor behavior, and (3) it could be that the factor is just statistical luck.

The stocks, which have a high book-to-market ratio, earn abnormal returns. One explanation could be that these firms are compensate for higher risk such as the risk of *financial distress* (Fama and French, 1993, 1995). Petkova and Zhang (2004) uses a conditional CAPM[15] to find an explanation of the value effect. He argue that 'valuable' firms (high book-to-market ratios) will have on average more tangible capital and therefore these firms are more vulnerable for economic downturns, because the lack of flexibility in the capacity. This explanation does not explain the whole value effect as said by Daniel and Titman (1997). Furthermore, it could be a proxy of *business cycle risk* according to Liew and Vassalou (2000) just like the size effect.

Value firms have shown bad results in the past and if investors extrapolate this bad performance the stock price will be too low. When the *overreaction* is corrected the returns are higher. This could be

[13] High minus Low

[14] France, Germany, Switzerland, U.K., Japan, U.S. , Europa and the global stock market.

[15] The parameters in the conventional CAPM can vary over time and co-vary in the conditional CAPM.

an explanation of the value effect according to Lakonishok, Shleifer and Vishny (1994)[16], also known as the *overreaction* hypothesis. This is also evidence of an inefficient market. According to Frankel and Lee (1998) investors make errors in market expectations of future earnings and this could be an explanation of the value effect.

The value effect is due to various selection biases[17], hence it is just *statistical luck*. These biases influence the empirical tests according to Kothari and Sloan (1994). However, these biases cannot explain the whole value effect. This is shown in the paper of Breen and Korajczyk (1994).

### CARHART FACTOR

Jagadeesh and Titman (1993) found that portfolios of the best performing stocks in most cases also outperform the other stocks in the following period. This suggests that there is a short horizon price momentum in both the aggregate market and across particular stocks. Note that the effect is a short term effect and it is even reversed in the long run (reversal effect). According to DeBondt and Thaler (1985) this is due to overreaction by investors. This is also evidence of the 'investor behavior' explanation of the size and value factor. Such overreaction results in positive abnormal return in the short term, but this overreaction will be corrected in the long run ("fads hypothesis"). This suggests an opposite investment strategy than suggested by Jagadeesh and Titman. However, this result could also be interpreted that the market risk premium varies over time. Hence, it also could be a rational reaction of investors to changes in discount rates.

Fama and French (1996) conclude that the three-factor model cannot explain the momentum effect. The model indicates even a reverse answer. Carhart (1997) suggest adding this momentum factor to the Fama French three-factor model, since the three-factor model cannot capture the momentum effect. However, because this factor is a short term effect, some question the power of predicting the cost of equity.

The fourth factor is computed by ranking stocks on the basis of their cumulative return over the past 11 months and then grouped into the top and bottom third of companies. Over the next month, a portfolio is formed that is the difference between the mean return of the top one-third and the mean return of the bottom one-third. The momentum effect is stronger for stocks that perform badly than stocks that perform well. Furthermore, the momentum effect is also stronger for small size firms.

### WORLD OR COUNTRY SPECIFIC THREE-FACTOR MODEL

In Griffin (2002) a world three-factor model is compared to country-specific three-factor models. According to Berk (2000) the importance of the size factor and value factor are depending a lot on using a world model or country-specific models. According to Griffin there are no benefits to extending the three-factor model at the world level. Country-specific models are more accurate and

[16] This theory is also supported by Chan, Karceski, and Lakonishok (2000) and La Porta, Lakanishok, Shleifer, Vishny (1997).

[17] Explained in the critique section.

explain more time-series variation than a world three-factor model. This is due to the fact that the country specific models have less out-of-sample and in-sample pricing errors.

***Equity Premium Puzzle***

Mehra and Prescott (1985,2003) conclude that the equity premium has been large relative to the risk aversion. The average risk aversion level found in experimental setting is not high enough to explain the equity premium. Using this risk aversion level, the equity premium should be less. This puzzle, known as the equity premium puzzle, has become very popular. The first explanation is the *difference between expected and realized returns*. Davis, Fama and French (2000) argue that using average realized returns to calculated the risk premium could be wrong. They show that the difference between realized and expected returns is the difference between the dividend growth and the capital gains rates. In the earlier period the dividend growth and capital gains were almost the same, however nowadays the capital gains significantly exceed the capital gains rate. The second explanation could be *survivorship bias*. Mehra and Prescott used the U.S. stock market in their paper of 1985. The U.S. has been proven to be the most successful capitalist system in the world, resulting in a (possible) survivorship bias. Furthermore, many markets are closed (permanently or during a period of time), but not the U.S. equity market. Not taking into account the stock markets that did not survive or did not performed that well will have as consequence that estimates of expected returns are overestimated.

***Critique***

According to Cochrane (2001), one of the problems using the Fama French three-factor model is survivorship bias and the existence of measurement errors. Furthermore, there could be potential biases in the test or other problems, namely (1) selection bias in data tapes, (2) measurement error in beta, (3) incorrect market portfolio proxy, and (4) the use of constant betas over time.

*Data mining concerns and data snooping bias*[18]

Already mentioned in the empirical evidence the value and size effect has been (partly) disappeared. The size effect disappeared after the early 1980s and the value effect became less effective after the early 1990s. According to Fischer Black it is a curious fact that some effects (such as the size effect and the January effect) disappear after they were discovered. When researches all over the world analyze data of returns over and over again with different explanatory variables, they will find such a variable (or patterns) eventually. The concern is that those patterns may fail when (basic) economic conditions change or when the patterns may be due to chance. However, if the finding exists in different markets and in different time periods, this would not be a concern anymore. According to Rouwenhorst (1999) the European evidence is very similar to findings of the Fama French three-factor model in the United States of America. This suggests that the model is not due to data mining. Furthermore, even if the data mining concerns are correct, the puzzle that value stocks yield on average higher returns than growth stocks still has to be explained.

[18] Lo and McKinlay (1990) and Black (1993).

*The use of portfolios*

In the tests, the stocks are sorted into different portfolios to reduce the measurement error and increase the statistical power of the test. However, grouping stocks using a variable that is correlated with the returns has as consequence that there is a lot of variation between groups and therefore the variation within the groups is rather small. As a result the test is biased and the chance that the test reject the null hypothesis that a flat beta-return relation is relatively low according to Berk (2000). Furthermore, it could be that the model is incorrectly tested. The tests focus on the alpha. Estimated alphas are equal to the measurement alpha and the sum of the true alphas. When sorting the stocks only on an empirical basis the cross-sectional relation between the alpha of a portfolio and the characteristic could be due to a correlation between the true alpha or the *measurement error* and the characteristic (Lo and McKinlay, 1990). This makes the test rather unreliable. Ang, Liu and Schwarz (2008) argue that using portfolios is incorrect. It increase the possibility that the alpha becomes insignificant, because the variation in betas is too small. They suggest to use individual stocks. However, it still does not imply that the factor effects are incorrect, because it still could be that there is a correlation between the factors and the true alphas.

*Incorrect proxy of the market portfolio*

According to Roll and Ross (1994) the only way to test the CAPM is to test whether the market portfolio is mean-variance efficient, but the real market portfolio is not observable. This is also known as the Roll critique.

Table 1: "The Roll critique"

| | Market proxy ex-post efficient | Market proxy ex-post inefficient |
|---|---|---|
| CAPM is true | Equation (2.1) holds | Equation (2.1) fails |
| CAPM is false | Equation (2.1) holds | Equation (2.1) fails |

As stated by Roll and Ross (1994), if the market proxy is inefficient equation (2.1) should always fail even when the CAPM is true. The equation always holds even if the CAPM is false when the market proxy is efficient. More generally, Black (1993) states that using a proxy for market portfolio that differs from the true market portfolio has as consequence that the betas are estimated with error. Stocks with a low beta will have a higher beta using the true market portfolio. According to Black the factor size is not relevant anymore.

This problem can be reduced using the generalized least squares (GLS) according to Kandel and Stambaugh (1995). However, GLS assumes that all the covariance parameters are identified and this assumption introduces further sampling error.

Jagannathan and Wang (1996) include human capital[19] in the market portfolio to avoid the Roll critique. The factor size becomes irrelevant when including human capital in the model. Hence, an extension of macro-economic factors within the model could result in more robustness results (such as the consumption-based CAPM (CCAPM) by Breeden (1979)).

Professional investors have difficulties to outperform proxies for the market (for example the S&P 500). This is one of the strongest evidence for CAPM and APT[20].

*The use of constant betas over time*

The model uses betas that are constant over time, however the risk of a firm is closely linked with the business cycle. Taking into account that the betas can vary over time, the new version of CAPM (also called Intertemporal CAPM of Merton (1973)) is able to explain about 30% of the cross-sectional return variation, without taking into account this time-variation it only explains 1% (Jagannathan and Wang, 1996). Furthermore, the factor size becomes insignificant and thus irrelevant. However, as said by Lewellen and Nagel (2006) time-variation in the betas cannot explain most known anomalies.

Pettengill, Sundaram, and Mathur (1995) also suggest that Fama and French should include the differences between the beta-return relationship during the good state and the bad state of the world in their three-factor model. The relation between beta and return is treated in the same way for the good state as the bad state of the world. Taking into account time-variation in the betas, they find a significant positive beta for the factor size in the good state and a significant negative beta in the bad state of the world. Furthermore, Pettengill, Sundaram, and Mathur found that the size effect is more relevant during the bad state. The conclusion is that the size effect is underestimated due to the assumption that the betas are the same for the good state and the bad state of the world.

Overall, the relevance of the Fama and French factors diminished if we include human capital and cyclical variation of betas. This critique will be (partly) further investigated in this paper. This is done by adding a variable to the Fama and French three-factor model which is closely related to the business cycle, namely innovation. This new factor will be discussed in detail in the next chapter.

[19] Using labor income as proxy for human capital.

[20] Bodie kane marcus, chapter 12

## III. INNOVATION

A new factor will be added in this research, namely innovation. In this chapter I discuss the relationship between innovation and the business cycle. As mentioned in the previous chapter, one of the explanations of the size and value factor is that the factors are proxies for business cycle risk. Secondly, I describe the effect of innovation on the risk premium of stocks. In this section a distinction is made between the different stages of the innovation process. Finally, I discuss the expected consequences when adding a new factor (innovation) to the Fama French three-factor model.

### A. INNOVATION AND THE BUSINESS CYCLE

Economic growth is broadly defined as the increasing capacity of the economy to satisfy the wants of its people (Kendrick, 1961). This growth is a result of increases in productivity, but also a result of new products and services.

Economic growth can be divided into growth in the short run and in the long run. Short term economic changes is referred as business cycle. These changes (mainly booms and recessions) are argued to be the cause of overproduction, overexpansion of credit, speculative bubbles and shocks (due to wars or political commotion). There are different theories that explains booms and crashes.

The business cycle moves up and down, creating fluctuations in the long-run trend in economic growth. Those long run fluctuations can be explained by different growth theories, such as (1) classical growth theory,(2) neoclassical growth model and (3) endogenous growth theory. According to the classical growth theory, productive capacity itself creates growth. So, increasing capital and improving capital will result in economic growth. In the neoclassical growth model the technology changes are crucial. Still, the capacity is important, but innovation is even more relevant according to this model. In line with the model, increases in capital relative to labor creates economic growth, because employees can be more productive. Furthermore, the economy of a country will reach a point, called steady state, where an increase in capital does not create economic growth anymore. This is due to the diminishing returns to capital. Countries can, with the help of innovation, overcome this steady state. The country can keep growing by innovation. New in the endogenous growth theory is the use of human capital instead of physical capital. Therefore economies never reach a steady state, because human capital has increasing rates of return. According to Helpman (2004) the focus in this theory is on increases in human capital (for example by education) and technological change (for example by innovation).

Peilei Fan (2011) found that the GDP growth in India and China during the period 1981 till 2004 (in particular in the 1990s) can be explained by innovation capacity. To strengthen their innovation capacity they invest in R&D and personnel, patents, and high-tech/service exports. Hence, by linking the science sector with the business sector, establishing incentives for innovative activities, and balancing the import of technology and indigenous R&D effort, both countries experienced a lot of economic growth in the last years. In line with this Helpman (2004) argue that innovation increases income per capita and also stimulates steady economic growth.

Hence, innovation is mentioned as one of the main drivers for economic growth. Innovation is also one of the main goals for governments to stimulate economic growth. Innovation is also needed to create jobs, because the most developed European countries are losing their competitive power to China and India.

### B. INNOVATION AND STOCK RETURNS

In accordance with Sood and Tellis (2009) the activities during an innovation can be divided in (1) the initiation, (2), development, and (3) commercialization of the product. The first activity includes events about alliances, funding, and expansions for new innovation projects. The second activity contains the work for prototypes, patents and preannouncements. The commercialization includes the launch of the new product and the awards for the quality of the product. Announcements about *initiation* of an innovation project can result into a positive return, because it could create new market expansions, deter competitor entry, improve probability of success, and enhance firms' competitive position (Arnand and Khanna, 2000). As stated by Kelm, Narayanan and Pinches (1995) and Crawford (1977) it also could lead to a negative return, because the investments are for a long horizon and are costly. This has as negative consequence that there is a high probability of failure and a lot of uncertainty. Notifications about the *development* of an innovation can result to either negative stock returns or positive stock returns. It could be that the announcement alert competitors of progress, reduce the element of surprise, trigger imitators and can lead to excessive discounting of the technological content. However, it could also reduce the uncertainty about the payoffs in the future of the innovation as said by Pakes (1985). Finally, the announcements about the *commercialization* of the innovation may lead to negative stock market rate of return, because the product is not fulfilling the expectations. Furthermore, the cost for promoting the product could be higher than expected (Crawford, 1977). On the other hand, the announcement could give a good signal of the competitiveness of the firm and the product could be a successful product, resulting in positive stock returns according to Tellis and Johnson (2007). Sood and Tellis (2009) investigate the effect of all the activities during an innovation on the stock market return. They control for the firm's announcement structure (size of the firm and age of the technology) and strategy (announcement frequency and research productivity). The return is highest for the announcements about the development stage (0.9%) and the lowest for commercialization (0.3%). The average return for initiation activities is 0.6%. The development stage has the greatest reduction of uncertainty and also captures some expected cash flows. This explains the high return for announcements about the development stage. At event level of development activities Sood and Tellis found that patents yield a return of 1.6%. Negative announcements result in negative returns. These returns are even higher in absolute value than positive returns. Overall, the development stage of a new product (i.e. innovation) yields the highest return. Patents are very important in the development stage. Hence, patents should be a good proxy for innovation.

Summarizing, the new factor innovation (measured by patents) can have a negative or positive effect on stock returns. It could be that it alert competitors of progress, reduce the element of surprise, trigger imitators and can lead to excessive discounting of the technological content. On the other hand, it could reduce the uncertainty about the payoffs in the future of the innovation. Alternatively, it could be that more innovation results in more intangibles relative to total assets. This could lead to more risky firms, because the value of intangibles are harder to value. Hence, it increases the risk premium and has a positive effect on stock returns.

### C. Innovation and Fama French three-factor model

As stated in the previous chapter, introducing time variation in betas results in insignificancy of the factor SMB. This suggests that the size factor is a proxy for business cycle risk. If this is the case, the size factor should not be significant in the regression. In this paper the underlying assumption is that patents are a good proxy for business cycle risk. Furthermore, we would expect that the loading on the patent factor is higher for small firms than for big firms. This is consistent with Sood and Tellis (2009). They conclude that good news about innovation becomes as a bigger surprise for small firms and therefore results into higher return. Additionally, Petkova (2006) argues that the size factor is related to innovations in variables that describe investment opportunities, such as the default spread.

Market values of companies can be different from their book value. This could be a result of the difference between the present value of their future abnormal earnings and the book value. Abnormal earnings are the results of monopoly power and/or innovation. Lev and Sougiannis (1999) found that 'growth' firms have large R&D capital, while 'valuable' firms have low R&D capital. Furthermore, they found that the ratio of R&D capital-to-market value is closely related to the book-to-market ratio. They also show that the return premium due to R&D is higher in the good state than in the bad state of the world. Basic research is riskier than development research (because of the technological feasibility) and therefore it should have a higher return premium. This theory is consistent with the findings of Lev et al. They conclude that the value effect is a risk compensation and not a security mispricing. Adding patents[21] to the Fama French three-factor model should reduce the predictive power of the value factor.

Liew and Vassalou (2000) conclude that there is a positive relation between the three factors and future economic growth. Additionally, Pettengill, Sundaram and Mathur (2002) show that the size effect differs across bull and bear markets. This is consistent with the hypothesis of Fama and French (1992,1993,1995) that the factors can be explained as state variables in the context of Merton's (1973) intertemporal capital asset pricing model (ICAPM). Hence, the factor size and the factor value should not be significant if we take into account the business cycle risk (and thus patents[22]). In this paper I will investigate whether the two factors can be rationally explained as business cycle risk.

[21] R&D is highly correlated with patents.

[22] The underlying assumption is that patents are a good proxy for business cycle risk.

## IV. DATA & METHODOLOGY

In this chapter the dataset of the base case will be described in detail. Information about other cases[23] are shown in the section robustness checks in chapter five.

### A. DATA

I merged two datasets, namely a dataset on the technological and financial characteristics of different countries, to determine the relationship between innovation and the risk premium of stocks. The dataset on technological characteristics are obtained from the United States Patent and Trademark Office (USPTO). The financial information is obtained from the Kenneth French website and additional information is downloaded from DataStream. I have obtained the data for ten European countries, namely Austria, Belgium, France, Germany, Ireland, Italy, Netherlands, Spain, Switzerland and United Kingdom.

The raw dataset is one of the alternative cases that will be discussed in more detail in chapter five. I have eliminated the extreme events in the excess returns by trimming the highest 1% and the lowest 1%. Regressions are very sensitive for extreme events and therefore the results can be different when taking extreme events into account. These extreme events could be a result of errors in the data from DataStream or in the calculations. Furthermore, those observations could be due to very extreme events. As mentioned in the section size effect in chapter two, Knez and Ready (1997) show that the size effect is driven by the 1% highest/smallest observations. Using a robust regression method to trim the extreme return observations they show that the size effect is not significantly positive, but negative. The size factor seems to be due to a very small part of the small firms that do extraordinary well. This dataset will be used in the base case and will be discussed in this chapter.

Furthermore, the dataset is separated into different periods, namely the run-up, boom, crash and aftermath of a crisis. Bubbles are normally divided into these four periods. During the period 1993 till 2011 there were two bubbles, namely the dot.com bubble and the recent credit crunch. More information is shown in appendix 1. The correlations between the different explanatory variables are presented in appendix 2.

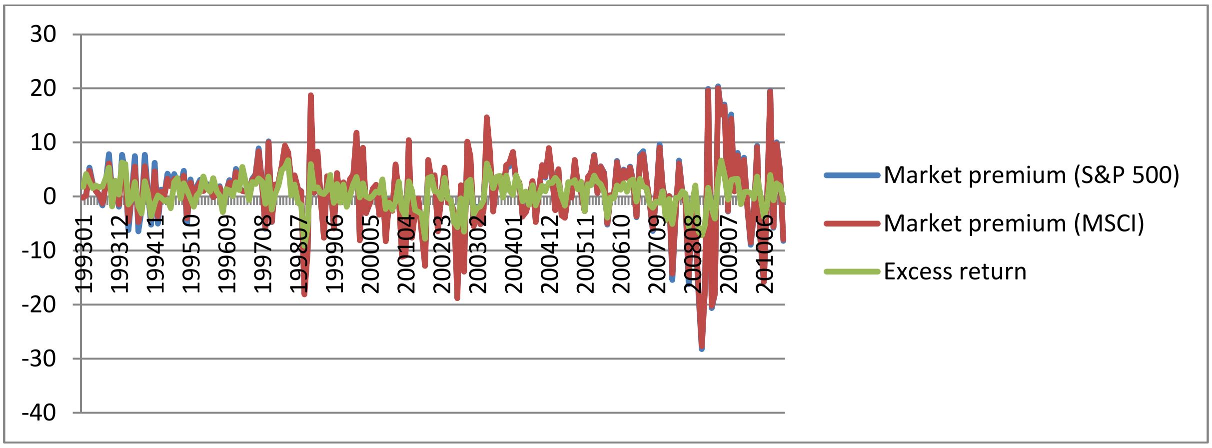
#### *FINANCIAL*

*Excess return*

The excess return is calculated by retrieving the return of all shares for each country from DataStream and subtracting the risk free rate from this to obtain the excess return. First, the average excess return will be compared with different proxies for the market premium.

[23] In these cases the dataset differs from the base case.

Figure 1: Monthly trend of average excess return and the market premium according to the MSCI index and the S&P index.




There is a rather strong relationship (correlation of 0.76) between the market premium and excess return. This is in line with the literature. However, the maximum and minimum of the variable excess return is more extreme than for the variable market premium. This could be a result of trimming the dataset, described in the previous section, but only the highest 1% and the lowest 1% is trimmed. The extreme events in the raw data is also a lot higher than an excess return of 20% and minus 30%.

Table 2 : Summary Statistics of the variable Excess Return

| | Companies | Observations | Mean | Median | Sd | Variance |
|---|---|---|---|---|---|---|
| Austria | 193 | 32166 | 0.19983 | -0.01250 | 6.61709 | 43.78582 |
| Belgium | 267 | 41157 | 0.42249 | -0.01083 | 6.61113 | 43.70704 |
| Switserland | 440 | 72689 | 0.51425 | -0.01167 | 6.80664 | 46.33031 |
| Germany | 353 | 41300 | 0.51595 | -0.00083 | 9.50405 | 90.32689 |
| Spain | 263 | 43230 | 0.49159 | -0.01167 | 6.70768 | 44.99293 |
| France | 119 | 20457 | 1.13642 | 0.97179 | 8.40412 | 70.62914 |
| United Kingdom | 616 | 99189 | 1.11418 | 0.99608 | 8.01809 | 64.28981 |
| Ireland | 156 | 24695 | 0.32265 | -0.01333 | 7.46309 | 55.69771 |
| Italy | 517 | 79601 | 0.04189 | -0.01833 | 6.97606 | 48.66543 |
| Netherlands | 364 | 62306 | 0.41552 | -0.01250 | 7.05199 | 49.73052 |
| Aftermath | | 134545 | 1.00842 | -0.00083 | 7.40181 | 54.78680 |
| Boom | | 78951 | 1.06591 | -0.03333 | 6.93712 | 48.12366 |
| Crash | | 130876 | -1.13352 | -0.02667 | 7.95426 | 63.27017 |
| Run-up | | 172418 | 1.17870 | -0.01750 | 7.04049 | 49.56849 |
| Total | 3288 | 516790 | 0.53157 | -0.01083 | 7.42433 | 55.12062 |

I have collected in total 516790 observations from 3288 companies. The maximum monthly excess return is 37.13% and the minimum is minus 29.33% for each country. This is due to the fact that I have trimmed the dataset. The mean of excess return is 0.53% during the period 1993 – 2010. We would expect overall a positive average excess return around two or five percent. The relatively low excess return could be due to the two crisis that occurred during 1993 till 2010, namely the dot.com crisis and the recent credit crisis. However, during the different periods of the crisis[24] there is still a relatively low average excess return. The standard deviation is the highest during the crash and the aftermath. It could be that the outliers significantly influence the average excess return. This could be an explanation of the unexpected findings about the average excess return during those periods. Furthermore, the median is for most countries negative, but the mean is positive. This is due to skewness in the dataset, meaning that the mean is driven by few successful firms. Two major European countries, namely France and United Kingdom have an average excess return that is more than 1%. One explanation could be that the companies in those countries are less vulnerable to negative shocks in the market. It also could be that they yield higher returns in the good state of the world. The reason behind the two explanations could be that the companies in those countries are good competitors relative to companies of other countries. However, another major country, namely Germany, does not give the same results.

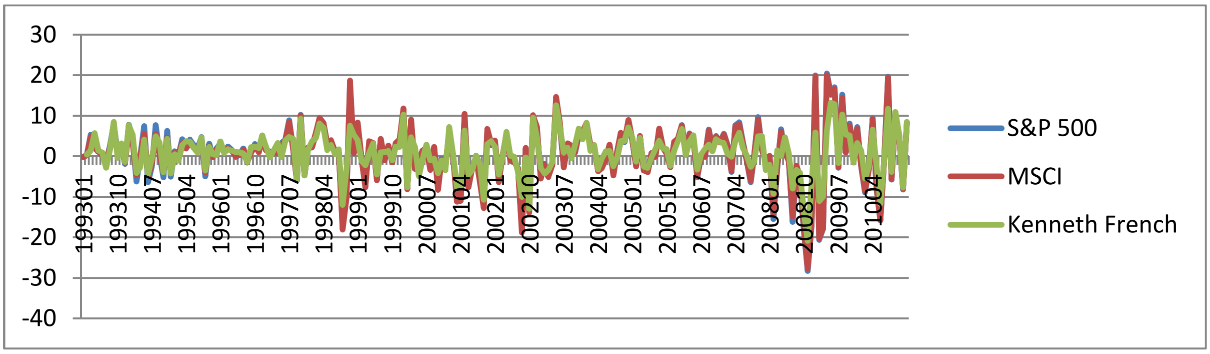
*Market premium*

As market portfolio I use the monthly market portfolio from the Kenneth French website during the period 1993-2010 resulting in 216 observations. The risk free rate is subtracted from the return on the market portfolio to obtain the market premium. All figures are in percentages. This market premium is compared with different indexes. First, it is compared with different proxies for the European market. The market premium according to the market portfolio obtained from the Kenneth French website is closely linked with the market premium according to the two indexes for the European market as shown in appendix 3. Second, the market portfolio is compared with the two main proxies for the market portfolio, namely the Standard and Poors 500 and the MSCI World. These proxies are frequently used in empirical research. For example, the monthly MSCI World index is often used as a common benchmark for 'world' or 'global' stock funds. This should be a good proxy for the market portfolio. The index is a free float-adjusted market capitalization weighted index that is designed to measure the equity market performance of developed markets[25].

[24] The run-up, boom, crash and the aftermath.

[25] www.msci,com

Figure 2: Monthly trend of various proxies for the World market portfolio




As shown in figure two, the market premium according to the market portfolio obtained from the Kenneth French website is highly correlated (0.95) with other proxies for the market premiums. This suggests that the conclusion resulting from the findings about the market premium in this paper are robust.

Table 3 : Summary Statistics of the variable Market Premium

| | Observations | Mean | Median | Sd | Variance | Range | Min | Max |
|---|---|---|---|---|---|---|---|---|
| Aftermath | 46 | 1.8755 | 1.3515 | 8.6833 | 75.4004 | 37.9499 | -17.9366 | 20.0133 |
| Boom | 31 | 2.1974 | 2.6016 | 5.5857 | 31.2002 | 26.8230 | -8.1272 | 18.6958 |
| Crash | 48 | -2.8465 | -1.2002 | 8.9058 | 79.3133 | 47.3015 | -27.7123 | 19.5892 |
| Run-up | 91 | 1.4535 | 1.6551 | 4.1571 | 17.2816 | 28.1516 | -18.1095 | 10.0421 |
| Total | 216 | 0.6946 | 1.0310 | 6.9552 | 48.3747 | 47.7257 | -27.7123 | 20.0133 |

As reported in Table 3 the expected the mean is the lowest and negative during the crash of a bubble. Overall the mean is positive, meaning that when exposed to systematic market risk it will result on average in a positive contribution on the return. This is in line with theory, because taking a position in the market portfolio should result in a higher risk premium[26] and therefore should result on average in a positive market premium. As shown in the previous section, the excess return is also positive. This is in line with the expectations that if the average excess return is positive the market premium is also positive and vice versa. The standard deviation is the highest during the bad state of the world, namely the crash and the aftermath. This is what we would expect and also found in the excess returns.

### *Value factor*

The factor HML is obtained from the Kenneth French website. This is computed by taking the average return on 50% of the stocks with the largest book-to-market ratio minus the average return on 50% of the stocks with the smallest book-to-market ratio. The value factor is provided monthly by Kenneth French and is calculated for the European market. This is collected for the period 1993 till 2010, resulting in 216 observations.

[26] Because the investor is more exposed to risk, namely market risk. The investor is only willing to be exposed to more risk when he gets a higher reward for this exposure.

Table 4 : Summary Statistics of the variable HML

| | Observations | Mean | Median | Sd | Variance | Range | Min | Max |
|---|---|---|---|---|---|---|---|---|
| Aftermath | 46 | 1.4909 | 0.6650 | 4.0726 | 16.5859 | 24.7400 | -4.3300 | 20.4100 |
| Boom | 31 | 0.0003 | 0.1800 | 3.4016 | 11.5710 | 17.4500 | -10.4000 | 7.0500 |
| Crash | 48 | -0.1515 | 0.7050 | 3.6537 | 13.3495 | 16.6600 | -6.9900 | 9.6700 |
| Run-up | 91 | 0.3215 | 0.4300 | 1.9215 | 3.6920 | 12.0000 | -4.9000 | 7.1000 |
| Total | 216 | 0.4194 | 0.4150 | 3.1460 | 9.8975 | 30.8100 | -10.4000 | 20.4100 |

As shown in Table 4, the value factor is on average positive, meaning that valuable firms will earn on average abnormal returns. During the boom it seems that there is not a big difference between stocks with a high market-to-book ratio and stocks with a low market-to-book ratio. During the crash the mean is negative, but during the aftermath, boom and the run-up it is positive. However, in all the periods the variable is sometimes positive and in some cases negative[27]. The standard deviation is the highest during the aftermath and the lowest during the run-up. During the aftermath the standard deviation is mostly due to extreme high events. Meaning that during the aftermath valuable firms earn in many cases a higher abnormal return.

### *Size factor*

This factor SMB is calculated using the MSCI index for Europe. I have subtracted the monthly MSCI index for small cap from the monthly MSCI index for large cap. The information is retrieved from DataStream. Due to limitation of available data, I used this method to determine the size factor[28]. As reported in Table 5, the standard deviation is the highest during the crash. Furthermore, it seems that the spread between small size firms and big size firms is higher during the boom and the crash.

Table 5 : Summary Statistics of the variable SMB

| | Observations | Mean | Median | Sd | Variance | Range | Min | Max |
|---|---|---|---|---|---|---|---|---|
| Aftermath | 46 | -984.370 | -1014.094 | 160.485 | 25755.420 | 536.430 | -1246.177 | -709.747 |
| Boom | 31 | -1405.232 | -1397.291 | 221.082 | 48877.410 | 652.870 | -1785.541 | -1132.671 |
| Crash | 48 | -1229.665 | -1219.252 | 313.180 | 98081.510 | 1082.079 | -1859.137 | -777.058 |
| Run-up | 91 | -815.180 | -706.812 | 299.089 | 89454.380 | 1011.442 | -1435.338 | -423.896 |
| Total | 216 | -1028.002 | -1031.111 | 346.804 | 120273.300 | 1435.241 | -1859.137 | -423.896 |

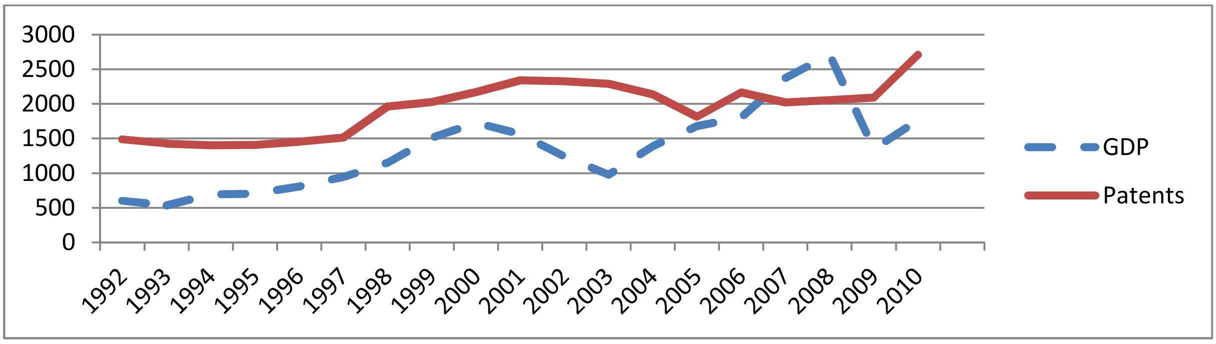
## *INNOVATION*

Due to effective intellectual property rights firms have an incentive to invest heavily in R&D and patents. As discussed in chapter three there is a relationship between the GDP and innovation. I will discuss the trend of GDP and patents. Furthermore, I describe the different proxies of innovation and finally the summary statistics of patents are also shown.

[27] In all periods the minimum is negative and the maximum is positive.

[28] Kenneth French does not provide this factor for the European market.

Figure 3: Annual trend of GDP and patents counts




Although the correlation is not very high (0.61), it seems that the GDP is linked with patents (also shown in figure three), especially in the 1990s. This is in line with the literature described in chapter three. However, it could also be that some other (unobserved) variable drives both of the variables GDP and patents. Hence, the correlation could be a spurious correlation. After this period the link between those two variables seem to diminish. Most of the theories argue that innovation plays a crucial role in the economic growth and more in general the business cycle.

*Proxies for innovation*

Innovation can be measured in two ways. First, by taking a proxy for the input of innovation and secondly by taking a proxy for the output of innovation.  Examples of innovation inputs are education policy, government and fiscal policy and the innovation environment. The output of innovation can be measured by patents, technology transfer, and other R&D results: business performance, such as labor productivity and total shareholder returns In this paper I will use as proxy for innovation an output variable, because this is more likely to explain stock returns.

Proxies for innovation are, for example, R&D, intangible assets, patents and number of researches in industrial research labs. R&D is an important explanatory variable to explain the market value. Patents add only a little in presence of R&D according to Griliches, Hall and Pakes (1987). The reason for this is the very skew distribution of patents. According to Nicholas (2008) there is a close correlation between patent stocks and reported intangibles. This is rather surprising given that intangible assets were capitalized in a highly subjective manner (Ely and Waymire, 1999). As said in chapter three patents yield the highest return in the development stage of innovation. Hence, patents should be a good proxy for innovation.

*Patents*

As proxy for innovation I will use patents. However, using patents counts as proxy for innovation is not looking at the quality of innovation[29]. Although studies have shown mostly constant results in market value equations using patents and independent measures of innovation (Blundell, Griffith, van Reenen, 1999), the literature is very clear that raw patent counts need to be quality adjusted

[29] There are also other limitations of patent data. Many inventions are not patented and the protection disclosure trade-off varies across industries (Moser, 2005).

before they can give correct information about the process of technological development (Hall, Jaffe, and Trajtenberg, 2005). Nevertheless, if patents rise relatively to the previous year it could be that the patents in the previous year were developed into economically feasible successful innovations resulting in more patents the next year (Trajtenberg, 1990). So, the frequency is assumed to be positively correlated with technological importance. Hence, the percentage change in patent counts will be a better explaining variable for innovation than just patent counts. This will also be done in this paper. Some researches use citation-weighted patents to adjust for the quality of the patents. Patents that are more cited are assumed to have a higher quality. In this paper, I do not use the citation-weighted patents, because this information is not publicly available. This is a limitation in this research.

Using records from the United States Patent and Trademark Office (USPTO) I found information for the period 1993 till 2010. Information about patents is yearly provided for all the ten countries used in this research, resulting in 180 total observations. For this period I collected 516.790 U.S. patents grants using the search engine of the European Patent Office (EPO). Furthermore, separate counts are provided for each patent type. There are four patent types, namely patents regarding utility (also called patents for invention), design, plant and reissue. In this paper the total patent counts are used. In Germany the mean of patents is the highest with 10.919 patents. This is a lot more than the second highest, namely France with 3.818 patents. There are some countries (such as Ireland, Spain and Austria) with a small number of patents[30]. As mentioned before I will use the percentage change in patents count.

Table 6 : Summary Statistics of the variable percentage change in patent counts

| | Observations | Mean | Median | Sd | Variance | Range | Min | Max |
|---|---|---|---|---|---|---|---|---|
| Austria | 18 | 0.05633 | 0.05077 | 0.15133 | 0.02290 | 0.48798 | -0.15174 | 0.33624 |
| Belgium | 18 | 0.05934 | 0.04502 | 0.14389 | 0.02070 | 0.50201 | -0.14897 | 0.35305 |
| Switserland | 18 | 0.02789 | 0.00951 | 0.12149 | 0.01476 | 0.51199 | -0.21281 | 0.29917 |
| Germany | 18 | 0.03928 | 0.01950 | 0.12177 | 0.01483 | 0.47447 | -0.15765 | 0.31682 |
| Spain | 18 | 0.08054 | 0.04251 | 0.17395 | 0.03026 | 0.73547 | -0.13961 | 0.59585 |
| France | 18 | 0.03168 | 0.00535 | 0.12675 | 0.01606 | 0.49769 | -0.15735 | 0.34034 |
| United Kingdom | 18 | 0.04189 | 0.02130 | 0.11027 | 0.01216 | 0.37141 | -0.08835 | 0.28306 |
| Ireland | 18 | 0.10476 | 0.11059 | 0.20282 | 0.04113 | 0.64190 | -0.18687 | 0.45503 |
| Italy | 18 | 0.03151 | 0.00556 | 0.12129 | 0.01471 | 0.46542 | -0.18243 | 0.28299 |
| Netherlands | 18 | 0.05136 | 0.01008 | 0.17914 | 0.03209 | 0.76339 | -0.21926 | 0.54413 |
| Aftermath | 30 | 0.08015 | 0.00778 | 0.16763 | 0.02810 | 0.58352 | -0.12849 | 0.45503 |
| Boom | 30 | 0.02060 | 0.01162 | 0.12410 | 0.01540 | 0.52341 | -0.18687 | 0.33654 |
| Crash | 40 | 0.04310 | 0.03716 | 0.08881 | 0.00789 | 0.45174 | -0.11551 | 0.33624 |
| Run-up | 80 | 0.05870 | 0.02134 | 0.16690 | 0.02786 | 0.81511 | -0.21926 | 0.59585 |
| Total | 180 | 0.05246 | 0.02134 | 0.14627 | 0.02139 | 0.81511 | -0.21926 | 0.59585 |

[30] Ranging from 136 - 524 patents.

As shown in Table 6 the mean of the variable patents is relatively high for the countries which have low absolute patents and vice versa. Furthermore, the median is for Switzerland, Spain, France, Italy and the Netherlands a lot different compared with their mean. It is due to the skewness.

The maximum of change in patents are during the aftermath and the run-up of bubbles higher than during the boom and crash. However, the minimum is during the run-up and the boom. The mean is the highest during the aftermath and the run-up of a bubble. This could be due to the fact that the *default risk* during this period is lower than during a boom or crash. Hence, patents could be a state variable that explains the value and size factor. The standard deviation is the highest during the run-up and the aftermath. The summary statistics of the raw patent counts are reported in appendix 4.

### B. METHODOLOGY

To obtain more understandable results and conclusions I constructed different portfolios[31]. The portfolios are sorted based on patents. Ideally, the companies are ranked each year on patents and each decile is formed into a portfolio, resulting in ten portfolios. However, as mentioned in the data section, patents are available at country level and not at company level. This means that ten countries are ranked. I will use two approaches to form the portfolios. The first approach (1) is based on raw patent counts and the second approach (2) is based on the percentage change in raw patent counts. For example, Austria has the highest percentage change in raw patent counts in 1993. After that, Ireland has the highest percentage change in raw patent counts in 1994. In 1995, the Netherlands have the highest percentage change in raw patent counts. Austrian stocks in 1993, Irish stocks in 1994 and Dutch stocks in 1995 will be formed into one portfolio. This is also done for the countries with the lowest percentage change in raw patent counts and everything in between. The composition about the portfolios are shown in appendix 5.

With the help of the portfolios I calculated the factor innovation. The factor innovation is calculated in two ways for each approach. The first method is using (1) the highest 30% of the countries en lowest 30% of the countries[32]. The second way is using (2) the highest and lowest 50% of the countries[33]. For example, (1) the average return on stocks with the 30% highest raw patent counts minus the average return on stocks with the 30% lowest raw patent counts and (2) the average return on stocks with the 50% highest raw patent counts minus the average return on stocks with the 50% lowest raw patent counts. So, in 1993, the average return of the lowest three portfolios (or the average return in three lowest countries[34]) based on percentage change in raw patent counts is subtracted from the average return of the highest three portfolios (or the average return in three highest countries[35]) based on percentage change in raw patent counts. The first method is the same as the computation of the size factor and the second method is computed in a similar way as the

[31] Fama and French (1993) also uses this to create more understandable results.

[32] In this case the highest and lowest three countries.

[33] In this case the highest and lowest five countries.

[34] The three lowest countries are Spain, Belgium and Italy.

[35] The three highest countries are Austria, Switzerland and Germany.

value factor. The summary statistics of the factor innovation is shown in appendix 6. In the next chapter the results of this new factor will be discussed in more detail.

Before discussing the results I would like to point out some limitations in this research. The first limitation is that there is no monthly data about patent counts[36]. Furthermore, data of patent counts are only available for the period 1993 till 2011. Additionally, patent counts are available at country level and not at firm level. Therefore, I did research at an international level and not country specific. As stated by Griffin (2002) there are no benefits to extending the three-factor model at the world level. Country-specific models are more accurate and explain more time-series variation than a world three-factor model. Finally, information about citation weighted patents are not publically available.

[36] Only annual data.

## V. Results

This chapter presents the results of the empirical research. The focus will be on discussion of the statistical and economic significance of the coefficients in different periods (during the run-up, boom, crash, and the aftermath) and a description of the economic intuition behind the tables. Finally, some checks are constructed to determine the robustness of the findings.

### A. Relationship between innovation and stock returns

To explore the relationship between innovation and stock returns, I will use multiple linear regressions. I regress the excess return of 3288 different companies on the factors of the Fama French three-factor model and the innovation factor. The regression can be expressed as follows:

$$R_{it} - R_{ft} = \alpha_i + \beta_{iM}\left(R_{Mt} - R_{ft}\right) + \beta_{is}SMB_t + \beta_{ih}HML_t + \beta_{il}Innovation_t + \varepsilon_{it} \qquad (5)$$

As discussed in the methodology section I used two approaches to form portfolios , namely (1) based on raw patent counts and (2) based on the percentage change in raw patent counts. Carhart (1997) regresses his four factor model on different portfolios. The portfolios are sorted based on the fourth factor, namely momentum effect. In this paper, regression (5) is performed for ten portfolios sorted on raw patent counts or percentage change in raw patent counts[37].

The innovation factors are calculated in two ways, namely (1) the average return on stocks with the 30% highest percentage change in patents minus the average return on stocks with the 30% lowest percentage change in patents and (2) the average return on stocks with the 50% highest percentage change in patents minus the average return on stocks with the 50% lowest percentage change in patents[38]. Hence, I will use in total four innovation factors. This is discussed in more detail in the previous section. First, I discuss the results using the CAPM and the Fama French three-factor model. Furthermore, I discuss the results using a four-factor model. In this model the factor innovation is added to the three-factor model. This model will be called FF3I .

As shown in Table 7, the r-square is around 8.5%. It measures the systematic risk. First, I regress for each portfolio the excess returns on the capital asset pricing model (1). Theory suggest that the beta of the market premium is close to one. This is not in line with the findings in Table 7 (average of 0.284). Previous empirical work, such as Fama and French (2004) also draw this conclusion. Another observation to point out is that the constant is highly significant in most cases. The constant or Jensen's alpha measures the abnormal return or pricing error above and beyond the rate of return expected by the model. Hence, if the CAPM is correct, the expectation is that alpha is equal to zero and thus insignificant. The findings show that this is not the case. It is even significant at 0.1% level in most cases. In all the regressions the constant is significantly positive. If the alpha is positive the security is underpriced and the price should rise. Secondly, I regress the excess returns on the Fama French three-factor model (2). The coefficient of the size factor is mostly significantly positive,

[37] This depends on the construction of the factor innovation.

[38] The same computation is done for the first approach (based on raw patent counts). In that case the 'percentage change in patents' is substituted by raw patent counts.

meaning that small cap stocks on average outperformed the large cap stocks. Also described in chapter two, I should expect a positive coefficient of the value factor. A positive value factor indicates that value stocks outperformed growth stocks. The findings of the Fama and French three-factor model (2) indicates that there is not a value premium in most cases. In line with the findings growth stocks significantly outperform value stocks in the dataset. Hence, this contradicts the literature. However, the value factor is not significant in all cases. The results are similar using portfolios based on raw patent counts (reported in appendix 7).

**Table 7: Results using the CAPM and the Fama French three-factor model**

*Dependent variable is the monthly excess return of around 3300 firms in the period of January 1993 until December 2010 within ten European countries, namely Austria, Belgium, France, Germany, Ireland, Italy, Netherlands, Spain, Switzerland and United Kingdom divided into ten portfolios. I trimmed the one percent highest and lowest observation of the dependent variable. Explanatory variables are the Fama and French three factors. The first (1) asset pricing model is the capital asset pricing model, the second (2) is the Fama French three-factor model. The stocks are formed into ten portfolios based on percentage change in patent counts. Alpha is the intercept of the model. The t-statistics are in parentheses.*

| Portfolio | Observations | Excess Return | CAPM (1) | | | Fama French three-factor model (2) | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | | | Alpha | Market | Adj R-sq | Alpha | Market | SMB | HML | Adj R-sq |
| 1 (high) | 49902 | 0.033 | 0.0631* | 0.271*** | 0.087 | 0.954*** | 0.273*** | 0.000794*** | -0.0233* | 0.088 |
| | | | (2.00) | (68.85) | | (8.48) | (67.60) | (8.21) | (-2.45) | |
| 2 | 47841 | 0.553 | 0.365*** | 0.209*** | 0.052 | 1.175*** | 0.211*** | 0.000780*** | -0.00645 | 0.053 |
| | | | (11.72) | (51.24) | | (11.83) | (50.53) | (8.60) | (-0.71) | |
| 3 | 59920 | 0.134 | 0.0271 | 0.321*** | 0.103 | 0.448*** | 0.327*** | 0.000362*** | -0.0660*** | 0.104 |
| | | | (0.94) | (83.17) | | (3.99) | (83.12) | (3.70) | (-7.29) | |
| 4 | 54471 | 0.760 | 0.567*** | 0.363*** | 0.093 | 1.165*** | 0.363*** | 0.000589*** | 0.0214* | 0.094 |
| | | | (17.96) | (74.75) | | (11.54) | (73.94) | (6.38) | (2.03) | |
| 5 | 50854 | 1.021 | 0.762*** | 0.343*** | 0.110 | 1.843*** | 0.348*** | 0.000935*** | -0.00921 | 0.111 |
| | | | (23.87) | (79.31) | | (14.71) | (78.80) | (8.94) | (-0.88) | |
| 6 | 51384 | 0.266 | 0.159*** | 0.322*** | 0.121 | 1.460*** | 0.331*** | 0.00110*** | -0.0729*** | 0.123 |
| | | | (5.11) | (83.95) | | (12.78) | (83.33) | (11.76) | (-7.22) | |
| 7 | 53091 | 0.567 | 0.432*** | 0.251*** | 0.066 | 1.215*** | 0.254*** | 0.000733*** | -0.0356*** | 0.067 |
| | | | (13.54) | (61.08) | | (11.63) | (60.70) | (7.78) | (-3.64) | |
| 8 | 61364 | 0.911 | 0.698*** | 0.307*** | 0.095 | 0.289** | 0.305*** | -0.000376*** | 0.0275** | 0.096 |
| | | | (23.20) | (80.50) | | (2.82) | (78.30) | (-4.05) | (3.27) | |
| 9 | 47900 | 0.459 | 0.280*** | 0.229*** | 0.056 | 1.424*** | 0.229*** | 0.00103*** | 0.0268** | 0.060 |
| | | | (9.24) | (53.53) | | (14.07) | (52.18) | (11.97) | (2.67) | |
| 10 (low) | 40063 | 0.589 | 0.382*** | 0.227*** | 0.049 | 1.360*** | 0.229*** | 0.000912*** | 0.0135 | 0.051 |
| | | | (10.98) | (45.41) | | (12.37) | (44.78) | (9.46) | (1.16) | |

t statistics in parentheses

* p<0.05, ** p<0.01, *** p<0.001

Table 8 reports the estimates of the FF3I model. Introducing the innovation factor based on raw patent counts increases the explanatory power of the model. Both of the innovation factors are generally statistically significant. Hence, it seems that a proxy for innovation, namely patents, can explain a part of stock returns. The positive beta suggests that stocks with a lot of patent counts (proxy of innovation) yields abnormal return in comparison to stocks with low patent counts. As stated by Sood and Tellis (2009) patents reduce the uncertainty about the payoffs in the future of the innovation. Alternatively, it could be that more innovation results in more intangibles relative to total assets. This could lead to more risky firms, because the value of intangibles are harder to value. Hence, it increases the risk premium and has a positive effect on stock returns. Also mentioned in the innovation section in chapter four, using patent counts as proxy for innovation is not looking at the quality of innovation. According to Hall, Jaffe, and Trajtenberg (2005) raw patent counts need to be quality adjusted before they can give correct information about the process of technological development. Nevertheless, if patents rise relatively to the previous year it could be that the patents in the previous year were developed into economically feasible successful innovations resulting in more patents the next year (Trajtenberg, 1990). So, the frequency is assumed to be positively correlated with technological importance. Hence, the percentage change in patent counts will be a better explaining variable for innovation than just patent counts. This is done in the Table 9. Alternatively citation-weighted patents are used to overcome this problem. However, this information is not publicly available. Introducing the innovation factor based on the percentage change in patent counts also increases the explanatory power of the model.

The results are consistent with the findings in the Table 8. However, the coefficient of the innovation factor (column 11 and 17) is mostly negative, meaning that factor innovation has a negative effect on stock returns. The explanation could be that it alerts competitors of progress, reduces the element of surprise, triggers imitators and can lead to excessive discounting of the technological content (Sood and Tellis, 2009). It is rather surprising that the beta of the factor innovation based on percentage change in patent counts is negative and that the beta of the factor innovation based on raw patent counts is positive. It could be that high quality patents (measured by percentage change in patents as described in chapter four) are treated differently. The argument that the patent alerts competitors of progress, reduces the element of surprise and triggers imitators could become more relevant for high quality patents. Furthermore, the economic and statistical significance of the size factor diminished when we introduce the innovation factor, but the significance of the value factor increases. This is partly what we expected. As described in chapter three the size and value factor are argued as proxies for business cycle risk. Liew and Vassalou (2000) found a positive relation between the three factors and the GDP growth. This is evidence that the factors could be a proxy of business cycle risk. The factor size and the factor value should not be significant if we take into account the business cycle risk (and thus patents[39]). Hence, adding this new factor should decrease the predictive power of the size and value factor. This contradicts with the findings of this research. It is even the other way around, it increases the relevance of the value factor. Assuming that patents is a good proxy for business cycle risk, it seems that the size and value factor cannot be explained by business cycle risk. However, the statistical significance diminishes a little bit for the size factor.

[39] The underlying assumption is that patents are a good proxy for business cycle risk.

## Table 8: Pricing of the innovation factor based on raw patent counts

*Dependent variable is the monthly excess return of around 3300 firms in the period of January 1993 until December 2010 within ten European countries, namely Austria, Belgium, France, Germany, Ireland, Italy, Netherlands, Spain, Switzerland and United Kingdom divided into ten portfolios. I trimmed the one percent highest and lowest observation of the dependent variable. Explanatory variables are the Fama and French three factors and an innovation factor. The first (1) asset pricing model is the capital asset pricing model. The table further reports the estimates of a four factor asset pricing model. In this model a new factor, namely innovation, is added to the Fama French three-factor model. The factor innovation used in this table is based on raw patent counts. In model (2) the factor is constructed using the 30% highest and 30% lowest stocks based on raw patent counts and in model (3) the highest/lowest 50% is used. The stocks are formed into ten portfolios based on raw patent counts. Alpha is the intercept of the model. The t-statistics are in parentheses.*

| Portfolio | Observations | Excess Return | CAPM (1) | | | FF model & innovation (2) | | | | | | FF model & innovation (3) | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | | Alpha | Market | Adj R-sq | Alpha | Market | SMB | HML | INNO (30%) | Adj R-sq | Alpha | Market | SMB | HML | INNO (50%) | Adj R-sq |
| 1 (high) | 24695 | 0.323 | 0.224*** | 0.173*** | 0.030 | 1.731*** | 0.174*** | 0.00144*** | -0.0197 | 0.0298 | 0.034 | 1.768*** | 0.174*** | 0.00145*** | -0.0208 | 0.0274 | 0.034 |
| | | | (4.78) | (27.66) | | (10.63) | (26.36) | (10.38) | (-1.34) | (1.68) | | (11.15) | (26.59) | (10.51) | (-1.40) | (1.66) | |
| 2 | 43230 | 0.492 | 0.364*** | 0.223*** | 0.061 | 1.852*** | 0.232*** | 0.00121*** | 0.0393*** | -0.105*** | 0.066 | 1.714*** | 0.231*** | 0.00116*** | 0.0426*** | -0.0922*** | 0.066 |
| | | | (11.60) | (52.81) | | (16.95) | (52.32) | (12.95) | (3.99) | (-8.84) | | (16.06) | (52.30) | (12.39) | (4.28) | (-8.31) | |
| 3 | 33884 | 0.214 | 0.121*** | 0.143*** | 0.028 | 0.13 | 0.139*** | 0.000134 | -0.0451*** | 0.0749*** | 0.029 | 0.226 | 0.140*** | 0.000171 | -0.0477*** | 0.0692*** | 0.029 |
| | | | (3.41) | (31.12) | | (1.02) | (28.85) | (1.24) | (-4.18) | (5.73) | | (1.83) | (29.15) | (1.59) | (-4.40) | (5.64) | |
| 4 | 39439 | 0.420 | 0.324*** | 0.203*** | 0.050 | 1.183*** | 0.206*** | 0.000784*** | -0.0186 | 0.00348 | 0.051 | 1.220*** | 0.209*** | 0.000786*** | -0.014 | -0.0278* | 0.052 |
| | | | (9.93) | (45.52) | | (10.34) | (43.46) | (8.12) | (-1.77) | (0.28) | | (10.93) | (44.47) | (8.15) | (-1.32) | (-2.38) | |
| 5 | 70212 | 0.560 | 0.415*** | 0.249*** | 0.073 | 0.782*** | 0.245*** | 0.000450*** | -0.0302*** | 0.0708*** | 0.074 | 0.887*** | 0.247*** | 0.000483*** | -0.0302*** | 0.0495*** | 0.074 |
| | | | (16.44) | (74.18) | | (8.74) | (69.10) | (5.92) | (-3.80) | (7.46) | | (10.16) | (70.16) | (6.37) | (-3.79) | (5.57) | |
| 6 | 64783 | 0.369 | 0.237*** | 0.229*** | 0.058 | 0.762*** | 0.224*** | 0.000602*** | -0.0114 | 0.0674*** | 0.059 | 0.834*** | 0.223*** | 0.000649*** | -0.0178* | 0.0851*** | 0.060 |
| | | | (8.96) | (63.12) | | (8.40) | (58.69) | (7.67) | (-1.36) | (6.57) | | (9.42) | (58.83) | (8.27) | (-2.10) | (8.96) | |
| 7 | 79601 | 0.042 | -0.101*** | 0.260*** | 0.079 | 0.422*** | 0.262*** | 0.000469*** | 0.00129 | -0.0068 | 0.079 | 0.370*** | 0.259*** | 0.000464*** | -0.00359 | 0.0278*** | 0.080 |
| | | | (-4.26) | (82.63) | | (5.01) | (78.45) | (6.59) | (0.17) | (-0.76) | | (4.52) | (77.99) | (6.53) | (-0.48) | (3.32) | |
| 8 | 67740 | 1.139 | 0.897*** | 0.442*** | 0.135 | 0.894*** | 0.430*** | 0.000463*** | -0.012 | 0.246*** | 0.140 | 1.303*** | 0.433*** | 0.000709*** | -0.0274** | 0.238*** | 0.140 |
| | | | (31.00) | (102.71) | | (9.15) | (98.79) | (4.74) | (-1.27) | (20.25) | | (13.23) | (99.69) | (7.06) | (-2.85) | (20.37) | |
| 9 | 51906 | 1.091 | 0.810*** | 0.409*** | 0.170 | 1.958*** | 0.397*** | 0.00110*** | -0.0145 | 0.104*** | 0.174 | 2.045*** | 0.397*** | 0.00111*** | -0.0169 | 0.102*** | 0.175 |
| | | | (24.90) | (103.18) | | (14.22) | (89.00) | (10.70) | (-1.47) | (8.65) | | (15.40) | (89.94) | (10.95) | (-1.71) | (9.15) | |
| 10 (low) | 41300 | 0.516 | 0.386*** | 0.422*** | 0.131 | 0.608** | 0.409*** | 0.000499*** | -0.107*** | 0.206*** | 0.136 | 0.842*** | 0.413*** | 0.000566*** | -0.109*** | 0.172*** | 0.135 |
| | | | (8.85) | (78.98) | | (3.19) | (71.13) | (3.32) | (-8.29) | (13.46) | | (4.50) | (72.05) | (3.77) | (-8.41) | (11.86) | |

t statistics in parentheses

* p<0.05, ** p<0.01, *** p<0.001

## Table 9: Pricing of the innovation factor based on percentage change in patent counts

*Dependent variable is the monthly excess return of around 3300 firms in the period of January 1993 until December 2010 within ten European countries, namely Austria, Belgium, France, Germany, Ireland, Italy, Netherlands, Spain, Switzerland and United Kingdom divided into ten portfolios. I trimmed the one percent highest and lowest observation of the dependent variable. Explanatory variables are the Fama and French three factors and an innovation factor. The first (1) asset pricing model is the capital asset pricing model. The table further reports the estimates of a four factor asset pricing model. In this model a new factor, namely innovation, is added to the Fama French three-factor model. The factor innovation used in this table is based on percentage change in patent counts. In model (2) the factor is constructed using the 30% highest and 30% lowest stocks based on percentage change in patent counts and in model (3) the highest/lowest 50% is used. The stocks are formed into ten portfolios based on percentage change in patent counts. Alpha is the intercept of the model. The t-statistics are in parentheses.*

| Portfolio | Observations | Excess Return | CAPM (1) | | | FF model & innovation (2) | | | | | | FF model & innovation (3) | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | | Alpha | Market | Adj R-sq | Alpha | Market | SMB | HML | INNO (30%) | Adj R-sq | Alpha | Market | SMB | HML | INNO (50%) | Adj R-sq |
| 1 (high) | 49902 | 0.033 | 0.0631* | 0.271*** | 0.087 | 0.807*** | 0.271*** | 0.000523*** | -0.0252** | -0.226*** | 0.091 | 0.646*** | 0.267*** | 0.000474*** | -0.0250** | -0.203*** | 0.091 |
| | | | (2.00) | (68.85) | | (7.14) | (66.97) | (5.27) | (-2.66) | (-11.94) | | (5.65) | (65.62) | (4.77) | (-2.64) | (-13.74) | |
| 2 | 47841 | 0.553 | 0.365*** | 0.209*** | 0.052 | 0.611*** | 0.209*** | -0.0000192 | 0.00723 | -0.356*** | 0.062 | 0.657*** | 0.208*** | 0.000208* | 0.00523 | -0.249*** | 0.061 |
| | | | (11.72) | (51.24) | | (5.95) | (50.44) | (-0.20) | (0.80) | (-20.66) | | (6.40) | (50.07) | (2.19) | (0.58) | (-19.00) | |
| 3 | 59920 | 0.134 | 0.0271 | 0.321*** | 0.103 | 0.581*** | 0.325*** | 0.000282** | -0.0771*** | -0.275*** | 0.108 | 0.508*** | 0.322*** | 0.000367*** | -0.0744*** | -0.260*** | 0.109 |
| | | | (0.94) | (83.17) | | (5.17) | (82.82) | (2.89) | (-8.51) | (-15.52) | | (4.53) | (81.99) | (3.76) | (-8.23) | (-17.50) | |
| 4 | 54471 | 0.760 | 0.567*** | 0.363*** | 0.093 | 1.016*** | 0.361*** | 0.000404*** | 0.0171 | -0.113*** | 0.094 | 0.776*** | 0.359*** | 0.000257** | 0.0148 | -0.196*** | 0.097 |
| | | | (17.96) | (74.75) | | (9.78) | (73.32) | (4.16) | (1.62) | (-6.09) | | (7.38) | (72.99) | (2.69) | (1.40) | (-12.90) | |
| 5 | 50854 | 1.021 | 0.762*** | 0.343*** | 0.110 | 1.811*** | 0.350*** | 0.00102*** | -0.0045 | 0.130*** | 0.112 | 1.871*** | 0.350*** | 0.000992*** | -0.00767 | 0.0893*** | 0.112 |
| | | | (23.87) | (79.31) | | (14.45) | (79.13) | (9.67) | (-0.43) | (6.97) | | (14.92) | (78.99) | (9.44) | (-0.73) | (5.50) | |
| 6 | 51384 | 0.266 | 0.159*** | 0.322*** | 0.121 | 1.503*** | 0.333*** | 0.00123*** | -0.0723*** | 0.135*** | 0.124 | 1.602*** | 0.336*** | 0.00127*** | -0.0749*** | 0.169*** | 0.125 |
| | | | (5.11) | (83.95) | | (13.14) | (83.63) | (12.88) | (-7.17) | (6.83) | | (13.94) | (84.05) | (13.33) | (-7.43) | (10.30) | |
| 7 | 53091 | 0.567 | 0.432*** | 0.251*** | 0.066 | 1.106*** | 0.253*** | 0.000528*** | -0.0367*** | -0.152*** | 0.068 | 1.067*** | 0.252*** | 0.000564*** | -0.0362*** | -0.106*** | 0.068 |
| | | | (13.54) | (61.08) | | (10.51) | (60.36) | (5.43) | (-3.77) | (-8.52) | | (10.01) | (60.10) | (5.80) | (-3.71) | (-6.95) | |
| 8 | 61364 | 0.911 | 0.698*** | 0.307*** | 0.095 | 0.604*** | 0.305*** | 0.000167 | 0.0288*** | 0.340*** | 0.102 | 0.764*** | 0.308*** | 0.000189 | 0.0273** | 0.274*** | 0.102 |
| | | | (23.20) | (80.50) | | (5.85) | (78.71) | (1.74) | (3.43) | (20.99) | | (7.30) | (79.40) | (1.96) | (3.26) | (20.78) | |
| 9 | 47900 | 0.459 | 0.280*** | 0.229*** | 0.056 | 1.391*** | 0.229*** | 0.000961*** | 0.0257* | -0.0833*** | 0.060 | 1.238*** | 0.226*** | 0.000897*** | 0.0265** | -0.186*** | 0.062 |
| | | | (9.24) | (53.53) | | (13.70) | (52.06) | (10.98) | (2.56) | (-4.17) | | (12.11) | (51.28) | (10.37) | (2.64) | (-12.10) | |
| 10 (low) | 40063 | 0.589 | 0.382*** | 0.227*** | 0.049 | 1.282*** | 0.228*** | 0.000779*** | 0.012 | -0.128*** | 0.052 | 1.248*** | 0.227*** | 0.000800*** | 0.0133 | -0.171*** | 0.053 |
| | | | (10.98) | (45.41) | | (11.57) | (44.54) | (7.84) | (1.04) | (-5.48) | | (11.29) | (44.29) | (8.25) | (1.15) | (-9.30) | |

t statistics in parentheses

* p<0.05, ** p<0.01, *** p<0.001

As said in the previous section, the Jensen's alpha measures the abnormal return above and beyond the rate of return expected by the model. The alpha is expected to be zero. The findings show a significantly positive alpha even at 0.1% level. The positive alpha means that the security is underpriced and the price should rise.

Besides the statistical significance, the economic significance of the independent variable is also relevant. In this case I will use one times the standard deviation to determine the economic significance, because a standard benchmark is not available. Assessing whether this change is small or large, the economic effect is divided by the mean of the dependent variable. The economic significance of the factor innovation based on raw patent counts is around 35%. For the factor based on the percentage change in patents it is around 20%.

Some researchers have data mining concerns and suggest data snooping biases described in the critique section in chapter two. As mentioned in that section when the findings exist in different markets and in different time periods, it would not be a concern anymore. The results in this research suggest that this critique is not very severe.

Finally, adding a new factor to the Fama French three-factor model is useful when it captures the fluctuation of the excess return between the different portfolios, which cannot be captured by the other three factors. There is not an obvious pattern between the excess return and the betas of the two innovation factors used in Table 8 and Table 9. The correlation between the excess return and the coefficients of the innovation factors based on raw patent counts are rather high in comparison with the size and value factor. The correlation is 0.57 and 0.55 for the innovation factors based on raw patent counts. This is a lot higher than a correlation of 0.16 for the size factor and 0.06 for the value factor. However, the correlation between the excess return and the betas of the market factor is high (0.76). For the innovation factors based on percentage change in patent counts, I found that the correlation between these innovation factors and the excess return is 0.47 and 0.55. Furthermore, the correlation between the excess return and the estimates of the Fama French three factor model is only minus 0.08 for the size factor and 0.63 for the value factor. The correlation between the excess return and the market factor is 0.22. Hence, it seems that a major part of the fluctuation in excess return is already captured by the Fama French three-factor model.

### B. RELATIONSHIP BETWEEN INNOVATION AND STOCK RETURNS IN DIFFERENT SUB PERIODS

In this section I discuss the relationship between innovation and stock returns in different sub periods. As mentioned in chapter four, the dataset is divided into four periods, namely the run-up, boom, crash and aftermath of a crisis. More information about the periods is shown in appendix 1. I regress for each period the original Fama French three-factor model and the FF3I model. In the FF3I model a new factor is added to the Fama French three-factor model, namely innovation.

# Table 10: Pricing of the innovation factor in different sub periods

*Dependent variable is the monthly excess return of around 3300 firms in the period of January 1993 until December 2010 within ten European countries, namely Austria, Belgium, France, Germany, Ireland, Italy, Netherlands, Spain, Switzerland and United Kingdom divided into ten portfolios. Furthermore, the portfolios are divided into four time periods, namely run-up, boom, crash and aftermath. More information about the time periods are shown in appendix 1. I trimmed the one percent highest and lowest observation of the dependent variable. Explanatory variables are the Fama and French three factors and an innovation factor. First, the results are reported of the Fama French three-factor model. The table further reports the estimates of a four factor asset pricing model. In this model a new factor, namely innovation, is added to the Fama French three-factor model. The factor innovation used in this table is based on percentage change in patent counts. The factor is constructed using the 50% highest and 50% lowest stocks based on percentage change in patent counts. The stocks are formed into ten portfolios based on percentage change in patent counts. Alpha is the intercept of the model. The t-statistics are in parentheses.*

| Sample period | Observations | Alpha | t-stat | Market | t-stat | SMB | t-stat | HML | t-stat | INNO | t-stat |
|---|---|---|---|---|---|---|---|---|---|---|---|
| **Three-factor Fama-French Benchmark** | | | | | | | | | | | |
| *Portfolio 1 (high)* | | | | | | | | | | | |
| Run-up | 15596 | 0.872*** | (5.36) | 0.365*** | (25.37) | 0.000125 | (0.73) | -0.0525 | (-1.65) | | |
| Boom | 6187 | -1.265* | (-1.97) | 0.193*** | (11.29) | -0.000792 | (-1.74) | -0.0364 | (-1.44) | | |
| Crash | 17253 | -1.039*** | (-3.90) | 0.289*** | (44.48) | -0.000418* | (-2.10) | 0.0609*** | (3.57) | | |
| Aftermath | 10866 | -0.711 | (-1.61) | 0.150*** | (20.47) | -0.00122** | (-2.80) | -0.0322* | (-2.09) | | |
| *Portfolio 5* | | | | | | | | | | | |
| Run-up | 10852 | 1.315*** | (5.06) | 0.570*** | (39.67) | 0.000899*** | (3.74) | 0.441*** | (11.55) | | |
| Boom | 11558 | 2.733*** | (6.86) | 0.289*** | (24.58) | 0.00127*** | (4.64) | 0.121*** | (5.98) | | |
| Crash | 10520 | 0.0256 | (0.10) | 0.196*** | (23.86) | 0.000420* | (2.11) | -0.0870*** | (-4.71) | | |
| Aftermath | 17924 | 1.021** | (2.64) | 0.359*** | (51.53) | -0.000383 | (-1.01) | -0.217*** | (-11.29) | | |
| *Portfolio 10 (low)* | | | | | | | | | | | |
| Run-up | 17441 | 0.947*** | (5.85) | 0.365*** | (29.72) | 0.000430* | (2.48) | 0.297*** | (10.24) | | |
| Boom | 6868 | 2.953*** | (5.42) | 0.259*** | (16.94) | 0.00180*** | (5.03) | -0.145*** | (-4.85) | | |
| Crash | 8534 | -0.283 | (-0.91) | 0.147*** | (15.44) | 0.000293 | (1.22) | -0.0354 | (-1.53) | | |
| Aftermath | 7220 | 0.0408 | (0.07) | 0.177*** | (18.39) | -0.000318 | (-0.57) | -0.0492* | (-2.28) | | |
| **Four-factor model (incl. innovation) benchmark** | | | | | | | | | | | |
| *Portfolio 1 (high)* | | | | | | | | | | | |
| Run-up | 15596 | 0.609*** | (3.64) | 0.373*** | (25.89) | 0.000171 | (1.00) | -0.0909** | (-2.81) | -0.222*** | (-6.67) |
| Boom | 6187 | 2.341** | (2.66) | 0.176*** | (10.15) | 0.00153* | (2.55) | 0.031 | (1.12) | -0.305*** | (-5.96) |
| Crash | 17253 | -1.025*** | (-3.65) | 0.289*** | (41.71) | -0.000406 | (-1.88) | 0.0625** | (3.12) | 0.006 | (0.15) |
| Aftermath | 10866 | -1.568** | (-3.18) | 0.149*** | (20.30) | -0.00223*** | (-4.41) | -0.0108 | (-0.66) | -0.142*** | (-3.93) |
| *Portfolio 5* | | | | | | | | | | | |
| Run-up | 10852 | 0.944*** | (3.32) | 0.571*** | (39.74) | 0.000719** | (2.91) | 0.425*** | (11.04) | -0.186** | (-3.24) |
| Boom | 11558 | 4.007*** | (7.16) | 0.280*** | (23.33) | 0.00207*** | (5.63) | 0.134*** | (6.5) | -0.118** | (-3.25) |
| Crash | 10520 | -0.0191 | (-0.07) | 0.194*** | (21.93) | 0.000388 | (1.87) | -0.0927*** | (-4.39) | -0.0259 | (-0.56) |
| Aftermath | 17924 | 0.729 | (1.48) | 0.358*** | (50.47) | -0.000717 | (-1.38) | -0.212*** | (-10.71) | -0.0404 | (-0.95) |
| *Portfolio 10 (low)* | | | | | | | | | | | |
| Run-up | 17441 | 0.799*** | (4.90) | 0.370*** | (30.13) | 0.000434* | (2.51) | 0.277*** | (9.55) | -0.217*** | (-7.18) |
| Boom | 6868 | 4.637*** | (6.86) | 0.243*** | (15.51) | 0.00284*** | (6.54) | -0.115*** | (-3.72) | -0.217*** | (-4.20) |
| Crash | 8534 | -0.474 | (-1.48) | 0.139*** | (13.65) | 0.000138 | (0.56) | -0.0650* | (-2.51) | -0.146* | (-2.54) |
| Aftermath | 7220 | -1.375* | (-2.09) | 0.174*** | (17.99) | -0.00200** | (-2.91) | -0.0175 | (-0.77) | -0.229*** | (-4.25) |

t statistics in parentheses

* $p<0.05$, ** $p<0.01$, *** $p<0.001$

Table 10 reports the estimates of the models in different sub periods. During the run-up the market factor and the innovation factor seems to be relevant. Especially, the market factor seems to be important. The findings during the run-up are in line with the overall findings described in the previous section[40]. However, the beta of the value factor is significantly positive during the run-up in two portfolios. Overall, the coefficient of the value factor is negative. The results during the boom are similar to the findings during the run-up. The coefficient of the value effect is also positive in the two portfolios. Furthermore, the relevance of the market factor seems to be less important during the boom than during the run-up. The size factor seems to be more relevant during the boom than during other periods.

The Jensen's alpha is in two cases insignificant during the crash. Furthermore, the factor innovation is less significant and even insignificant. The market factor seems to be less relevant during the crash. Pettengill, Sundaram and Mathur (1995) found a significant positive beta for the factor size in the good state and a significant negative beta in the bad state of the world. This is in line with the findings reported in Table 10. Furthermore Pettengill et al found that the size effect is more relevant during the bad state. This cannot be supported with the results.

Summarizing, the main findings described in the previous section are consistent with the findings in different sub periods. Furthermore, the market factor is more relevant during the run-up of a crisis. The value factor seems to be important during the run-up. As said in the previous section it seems that the size and value factor are not a proxy for business cycle risk. However, as shown in Table 10, especially the coefficient of the size factor fluctuates between the different periods. The factor is mostly significantly positive during the good state (i.e. boom and run-up) and significantly negative during the bad state (i.e. crash and aftermath) of the world. So, it seems that size effect is still time varying and the new factor innovation does not fully capture this. The value factor does not give a clear result on this matter. The size factor seems to be an important factor during the boom. According to Pettengill, Sundaram and Mathur (1995) the coefficient of the size factor is significant positive in the good state and significant negative in the bad state of the world. They also found that the size effect is more relevant during the bad state. This is not in line with the results.

The beta of the factor innovation based on percentage change in patent counts is in all periods negative. Hence, the findings are in line with the overall findings, discussed in the previous section. However, this factor losses his statistical power during the crash. The factor seems to be more relevant during the good state of the world. As stated in chapter three, Lev and Sougiannis (1999) show that the return premium due to R&D is higher in the good state than in the bad state of the world. So, I would expect, due to high correlation between R&D and patents, that the coefficient during the good state is higher than during the bad state of the world. This is not consistent with the results presented in Table 10.

[40] Presented in Table 9.

### C. Robustness checks

As described in chapter four, decisions are made about the dataset. I have eliminated the extreme events in the excess returns by trimming the highest 1% and the lowest 1%. These extreme events could be a result of computation errors. This decision could have a major effect on the results. In this section the results are described using the raw datasets. The maximum of excess return is 315,26% and the minimum is minus 100,01%. The results using the raw dataset are reported in Table 11 and 12. The results are similar to the results using the trimmed dataset[41]. However, using the raw dataset, the asset pricing models are less statistically relevant. The conclusion is that outliers influences the regressions a lot in terms of the statistical significance. Summarizing, the main findings using the raw dataset are similar to the findings if I use the trimmed dataset, however the significance reduces. Furthermore, adding the new factor to the Fama French three-factor model is useful when it captures the fluctuations of the excess return between the different portfolios, which cannot be captured by the other three factors. The correlation between the excess returns and the coefficients of the innovation factor based on raw patent counts are respectively -0.90 and -0.87. This is very high, however the correlation between the three other factors (market, size and value factor) and the excess return is even higher, namely 0.93, 0.95 and -0.95. Based on percentage change in patents it is only -0.16 and -0.12. The correlation between the excess return and the three factors (market, size and value) is -0.13, 0.68 and -0.80. Hence, it seems that the most of the fluctuation in excess return is already captured by the Fama French three-factor model. In appendix 8, the estimates are reported for the Fama French three-factor model.

[41] Reported in Table 8 and 9.

## Table 11: Pricing of the innovation factor based on raw patent counts (using raw dataset)

*Dependent variable is the monthly excess return of around 3300 firms in the period of January 1993 until December 2010 within ten European countries, namely Austria, Belgium, France, Germany, Ireland, Italy, Netherlands, Spain, Switzerland and United Kingdom divided into ten portfolios.. Explanatory variables are the Fama and French three factors and an innovation factor. The first (1) asset pricing model is the capital asset pricing model. The table further reports the estimates of a four factor asset pricing model. In this model a new factor, namely innovation, is added to the Fama French three-factor model. The factor innovation used in this table is based on raw patent counts. In model (2) the factor is constructed using the 30% highest and 30% lowest stocks based on raw patent counts and in model (3) the highest/lowest 50% is used. The stocks are formed into ten portfolios based on raw patent counts. Alpha is the intercept of the model. The t-statistics are in parentheses.*

| Portfolio | Observations | Excess Return | CAPM (1) | | | FF model & innovation (2) | | | | | | FF model & innovation (3) | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | | Alpha | Market | Adj R-sq | Alpha | Market | SMB | HML | INNO (30%) | Adj R-sq | Alpha | Market | SMB | HML | INNO (50%) | Adj R-sq |
| 1 (high) | 24695 | 0.769 | 0.609*** | 0.282*** | 0.022 | 2.563*** | 0.274*** | 0.00202*** | -0.0222 | 0.131*** | 0.025 | 2.707*** | 0.273*** | 0.00209*** | -0.03 | 0.139*** | 0.025 |
| | | | (6.81) | (23.65) | | (8.26) | (21.73) | (7.67) | (-0.79) | (3.87) | | (8.95) | (21.86) | (7.93) | (-1.06) | (4.42) | |
| 2 | 43230 | 0.853 | 0.685*** | 0.293*** | 0.031 | 2.747*** | 0.303*** | 0.00172*** | 0.0615*** | -0.122*** | 0.034 | 2.587*** | 0.301*** | 0.00166*** | 0.0651*** | -0.106*** | 0.034 |
| | | | (11.69) | (37.14) | | (13.43) | (36.47) | (9.83) | (3.33) | (-5.46) | | (12.96) | (36.48) | (9.49) | (3.50) | (-5.11) | |
| 3 | 33884 | 0.721 | 0.567*** | 0.234*** | 0.009 | 0.294 | 0.218*** | 0.000146 | -0.0594 | 0.223*** | 0.010 | 0.578 | 0.220*** | 0.000258 | -0.0672* | 0.207*** | 0.010 |
| | | | (5.50) | (17.54) | | (0.80) | (15.46) | (0.47) | (-1.89) | (5.86) | | (1.61) | (15.69) | (0.82) | (-2.13) | (5.80) | |
| 4 | 39439 | 0.708 | 0.584*** | 0.265*** | 0.026 | 1.317*** | 0.261*** | 0.000748*** | -0.00917 | 0.0518* | 0.026 | 1.414*** | 0.265*** | 0.000773*** | -0.00625 | 0.0157 | 0.026 |
| | | | (9.74) | (32.40) | | (6.27) | (30.11) | (4.21) | (-0.47) | (2.24) | | (6.89) | (30.79) | (4.36) | (-0.32) | (0.73) | |
| 5 | 70212 | 1.060 | 0.880*** | 0.308*** | 0.002 | 0.884 | 0.300*** | 0.0000335 | 0.0974 | -0.000141 | 0.002 | 0.900 | 0.301*** | 0.0000335 | 0.0995 | -0.0136 | 0.002 |
| | | | (5.02) | (13.21) | | (1.42) | (12.15) | (0.06) | (1.77) | (-0.00) | | (1.48) | (12.28) | (0.06) | (1.79) | (-0.22) | |
| 6 | 64783 | 0.877 | 0.688** | 0.329*** | 0.001 | 1.925* | 0.322*** | 0.00131 | -0.00582 | 0.0905 | 0.001 | 1.997* | 0.318*** | 0.00139 | -0.0193 | 0.146 | 0.001 |
| | | | (2.78) | (9.72) | | (2.27) | (9.04) | (1.79) | (-0.07) | (0.95) | | (2.42) | (8.99) | (1.89) | (-0.24) | (1.65) | |
| 7 | 79601 | 0.367 | 0.171*** | 0.357*** | 0.052 | 0.741*** | 0.354*** | 0.000550*** | 0.0350** | 0.00923 | 0.052 | 0.687*** | 0.349*** | 0.000552*** | 0.0267* | 0.0610*** | 0.053 |
| | | | (4.19) | (66.04) | | (5.14) | (61.82) | (4.51) | (2.72) | (0.60) | | (4.88) | (61.39) | (4.53) | (2.07) | (4.25) | |
| 8 | 67740 | 1.485 | 1.199*** | 0.521*** | 0.013 | 1.050** | 0.504*** | 0.000467 | 0.0328 | 0.317*** | 0.014 | 1.585*** | 0.507*** | 0.000800* | 0.012 | 0.313*** | 0.014 |
| | | | (10.36) | (30.32) | | (2.68) | (28.85) | (1.19) | (0.86) | (6.50) | | (4.01) | (29.11) | (1.99) | (0.31) | (6.69) | |
| 9 | 51906 | 1.272 | 0.877*** | 0.574*** | 0.154 | 2.189*** | 0.544*** | 0.00138*** | 0.0403** | 0.193*** | 0.159 | 2.330*** | 0.543*** | 0.00139*** | 0.0353* | 0.193*** | 0.159 |
| | | | (18.08) | (97.10) | | (10.66) | (81.71) | (9.00) | (2.73) | (10.71) | | (11.77) | (82.49) | (9.20) | (2.39) | (11.63) | |
| 10 (low) | 41300 | 4.477 | 4.307 | 0.552 | 0.000 | 27.08 | 0.901 | 0.0164 | -1.445 | -1.489 | 0.000 | 24.58 | 0.846 | 0.0155 | -1.461 | -0.993 | 0.000 |
| | | | (1.22) | (1.28) | | (1.76) | (1.93) | (1.35) | (-1.38) | (-1.20) | | (1.62) | (1.82) | (1.28) | (-1.39) | (-0.85) | |

t statistics in parentheses

* $p<0.05$, ** $p<0.01$, *** $p<0.001$

## Table 12: Pricing of the innovation factor based on percentage change in patent counts (using raw dataset)

*Dependent variable is the monthly excess return of around 3300 firms in the period of January 1993 until December 2010 within ten European countries, namely Austria, Belgium, France, Germany, Ireland, Italy, Netherlands, Spain, Switzerland and United Kingdom divided into ten portfolios. Explanatory variables are the Fama and French three factors and an innovation factor. The first (1) asset pricing model is the capital asset pricing model. The table further reports the estimates of a four factor asset pricing model. In this model a new factor, namely innovation, is added to the Fama French three-factor model. The factor innovation used in this table is based on percentage change in patent counts. In model (2) the factor is constructed using the 30% highest and 30% lowest stocks based on percentage change in patent counts and in model (3) the highest/lowest 50% is used. The stocks are formed into ten portfolios based on percentage change in patent counts. Alpha is the intercept of the model. The t-statistics are in parentheses.*

| Portfolio | Observations | Excess Return | CAPM (1) | | | FF model & innovation (2) | | | | | | FF model & innovation (3) | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | | Alpha | Market | Adj R-sq | Alpha | Market | SMB | HML | INNO (30%) | Adj R-sq | Alpha | Market | SMB | HML | INNO (50%) | Adj R-sq |
| 1 (high) | 49902 | 0.105 | 0.149** | 0.393*** | 0.062 | 0.952*** | 0.391*** | 0.000565** | -0.018 | -0.247*** | 0.064 | 0.755*** | 0.386*** | 0.000490** | -0.0179 | -0.236*** | 0.064 |
| | | | (2.72) | (57.52) | | (4.85) | (55.76) | (3.28) | (-1.09) | (-7.52) | | (3.80) | (54.76) | (2.84) | (-1.09) | (-9.20) | |
| 2 | 47841 | 1.179 | 0.909** | 0.301*** | 0.001 | 1.72 | 0.296*** | 0.0004940 | 0.0692 | -0.430* | 0.001 | 2.06 | 0.295*** | 0.00108 | 0.0603 | -0.164 | 0.001 |
| | | | (2.74) | (6.91) | | (1.57) | (6.65) | (0.47) | (0.72) | (-2.33) | | (1.88) | (6.64) | (1.06) | (0.62) | (-1.17) | |
| 3 | 59920 | 0.336 | 0.185** | 0.453*** | 0.049 | 0.951*** | 0.455*** | 0.000416* | -0.0547** | -0.366*** | 0.050 | 0.854*** | 0.451*** | 0.000529* | -0.0511** | -0.344*** | 0.051 |
| | | | (3.01) | (55.33) | | (3.99) | (54.52) | (2.00) | (-2.84) | (-9.72) | | (3.59) | (53.98) | (2.55) | (-2.66) | (-10.89) | |
| 4 | 54471 | 1.348 | 1.105*** | 0.457*** | 0.006 | 2.114*** | 0.454*** | 0.00102* | 0.107 | -0.006 | 0.006 | 1.819** | 0.450*** | 0.000774 | 0.102 | -0.152 | 0.006 |
| | | | (6.53) | (17.60) | | (3.80) | (17.20) | (1.97) | (1.89) | (-0.06) | | (3.22) | (17.08) | (1.51) | (1.80) | (-1.87) | |
| 5 | 50854 | 1.354 | 1.016*** | 0.448*** | 0.083 | 2.462*** | 0.456*** | 0.00143*** | 0.0315* | 0.201*** | 0.086 | 2.546*** | 0.456*** | 0.00138*** | 0.0262 | 0.115*** | 0.085 |
| | | | (20.86) | (68.02) | | (12.88) | (67.64) | (8.92) | (1.97) | (7.06) | | (13.32) | (67.44) | (8.59) | (1.64) | (4.63) | |
| 6 | 51384 | 0.430 | 0.281*** | 0.447*** | 0.084 | 2.292*** | 0.461*** | 0.00188*** | -0.0853*** | 0.241*** | 0.087 | 2.478*** | 0.468*** | 0.00195*** | -0.0900*** | 0.313*** | 0.088 |
| | | | (5.32) | (68.54) | | (11.77) | (68.15) | (11.51) | (-4.97) | (7.18) | | (12.67) | (68.78) | (12.04) | (-5.25) | (11.22) | |
| 7 | 53091 | 3.844 | 3.699 | 0.268 | 0.000 | 9.077 | 0.373 | 0.00437 | -1.198 | -0.409 | 0.000 | 8.927 | 0.371 | 0.00441 | -1.197 | -0.318 | 0.000 |
| | | | (1.35) | (0.76) | | (1.00) | (1.03) | (0.52) | (-1.43) | (-0.27) | | (0.97) | (1.02) | (0.53) | (-1.42) | (-0.24) | |
| 8 | 61364 | 1.566 | 1.293*** | 0.393*** | 0.005 | 0.166 | 0.381*** | -0.000685 | 0.142** | 0.451*** | 0.006 | 0.447 | 0.385*** | -0.000575 | 0.140** | 0.404*** | 0.006 |
| | | | (7.53) | (18.03) | | (0.28) | (17.13) | (-1.24) | (2.95) | (4.87) | | (0.74) | (17.32) | (-1.04) | (2.91) | (5.34) | |
| 9 | 47900 | 0.730 | 0.494*** | 0.302*** | 0.023 | 1.967*** | 0.302*** | 0.00133*** | 0.0354 | 0.0125 | 0.024 | 1.852*** | 0.300*** | 0.00124*** | 0.0351 | -0.109*** | 0.024 |
| | | | (7.72) | (33.40) | | (9.16) | (32.51) | (7.18) | (1.67) | (0.30) | | (8.56) | (32.21) | (6.78) | (1.65) | (-3.35) | |
| 10 (low) | 40063 | 0.971 | 0.669*** | 0.330*** | 0.026 | 1.910*** | 0.332*** | 0.00113*** | 0.0266 | -0.0701 | 0.027 | 1.822*** | 0.329*** | 0.00107*** | 0.0272 | -0.200*** | 0.028 |
| | | | (9.60) | (32.98) | | (8.59) | (32.30) | (5.65) | (1.15) | (-1.50) | | (8.21) | (32.07) | (5.49) | (1.17) | (-5.41) | |

t statistics in parentheses

* p<0.05, ** p<0.01, *** p<0.001

## VI. Conclusions

This paper contributes to the debate which (risk) factors can explain stock returns. The paper focused on the following hypotheses: (1) innovation explain stock returns, (2) the relevance of the size factor and the value factor diminishes when we introduce the innovation factor and (3) the results are not similar between different time periods. With this research I hope to give more insights to the relationship between risk and returns of stocks.

In this paper I used patents as proxy for innovation. According to Hall, Jaffe, and Trajtenberg (2005) raw patent counts need to be quality adjusted. Normally, citation-weighted patents are used to overcome this problem. However, this information is not publicly available. Alternatively, percentage change in patent counts can be used (Trajtenberg, 1990). The frequency is assumed to be positively linked with technological importance, meaning that if patents rise relatively to the previous year it is due to the economically successful innovations in the previous year.

I found that the new factor innovation, based on raw patent counts and percentage change in patent counts, can explain stock returns in the period 1993 till 2010. The positive beta of the factor innovation based on raw patent counts implies that stocks with a lot of patent counts yield abnormal return in comparison to stocks with low patent counts. An explanation of the positive beta is that patents increase the confidence about the cash flows in the future of the innovation (Sood and Tellis, 2009). Another explanation could be that more innovation result in more intangibles relative to total assets. This influence the risk profile of firms, because the value of intangibles is hard to determine in most cases. Hence, it increases the risk premium and has a positive effect on stock returns. However, the coefficient of the factor innovation based on percentage change in patent counts is negative. An explanation for this negative coefficient could be that it alert competitors of progress. This could initiate imitators by competitors and also reduce the element of surprise. It is remarkable that the beta of the factor innovation is negative using percentage change in patent counts as proxy for innovation, but positive using raw patent counts as proxy for innovation. It could be that the argument that patents alert competitors of progress is more relevant for high quality patents. Adding the new factor to the Fama French three-factor model is useful when it captures the co-movement of the excess return of different portfolios, which cannot be captured by the other three factors. There is not a strong link between the excess return and the beta of the innovation factor. Hence, most part of the fluctuation in excess return is already captured by the Fama French three-factor model

Secondly, I found that the relevance of the size factor diminishes when we introduce the innovation factor, but the significance of the value factor increases. Liew and Vassalou (2000) found a positive relation between the three factors and the GDP growth. They argue that this is evidence that the factors are a proxy of business cycle risk. If we take into account business cycle risk in the regression, the factor size and the factor value should not be significant anymore. Assuming that patents is a good proxy for business cycle risk, the predictive power of the size and value factor should diminish. This is not in line with the findings.

Finally, I find that the coefficients of the factor innovation does not vary a lot over time. The factor is more relevant during the good state of the world and not important during the aftermath. As stated in chapter three, Lev and Sougiannis (1999) show that the return premium due to R&D is higher in the good state than in the bad state of the world. So I would expect, due to high correlation between R&D and patents, that the coefficient during the good state is higher than during the bad state of the world. This is not consistent with the findings. Furthermore, as said in the previous paragraph it seems that the size and value factor is not a proxy for business cycle risk. However, the coefficient of the size factor fluctuates between the different sub periods. The factor is significantly positive during the boom and run-up and significantly negative during the crash and aftermath of the world. So, it seems that the value effect is still time varying and the new factor innovation does not fully capture this. The size factor seems to be an important factor during the boom. According to Pettengill, Sundaram and Mathur (1995) the coefficient of the size factor is significant positive in the good state and significant negative in the bad state of the world. They also found that the size effect is more relevant during the bad state. This is not in line with the findings.

Recommendations for future research could be based on using other innovation proxies, such as citation-weighted patents, to explain stock returns. Additionally, I would to recommend to do research at an country level and not at an international level. Even evidence from different discourse is possible. For that reason, innovative ideas are welcome and further research is needed to supplement the current literature regarding explaining stock returns.

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## Appendix 1: Time periods

| Crisis | Description | Date |
|---|---|---|
| The dot.com crisis | 'run-up' | January 1992 till November 1998 |
| | 'boom' | November 1998 till March 2000 |
| | 'crash' | March 2000 till October 2002 |
| | 'aftermath' | October 2002 till October 2004 |
| The recent credit crisis | 'run-up' | October 2004 till July 2006 |
| | 'boom' | July 2006 till October 2007 |
| | 'crash' | October 2007 till March 2009 |
| | 'aftermath' | March 2009 till January 2011 |

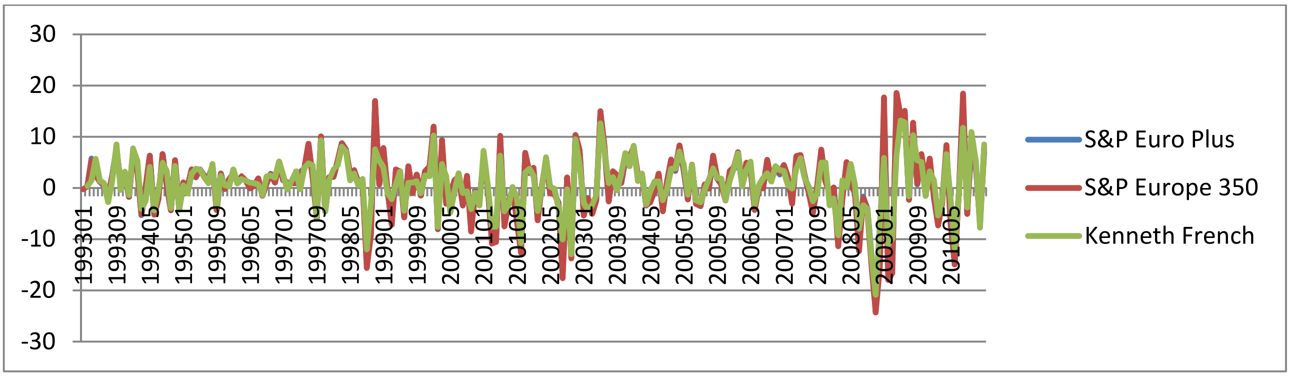
## Appendix 2: Correlation of the (in)dependent variables

| | | Excess return | Market premium | Size factor | Value factor | Innovation* (30%-30%) | Innovation* (50%-50%) | Innovation** (30%-30%) | Innovation** (50%-50%) |
|---|---|---|---|---|---|---|---|---|---|
| Excess return | | 1 | | | | | | | |
| Market premium | | 0.288 | 1 | | | | | | |
| Size factor | | 0.0158 | -0.0409 | 1 | | | | | |
| Value factor | | 0.0589 | 0.1974 | 0.1292 | 1 | | | | |
| Innovation* | (30%-30%) | 0.1138 | 0.2809 | 0.064 | 0.1801 | 1 | | | |
| Innovation* | (50%-50%) | 0.1097 | 0.2652 | 0.0113 | 0.2123 | 0.9531 | 1 | | |
| Innovation** | (30%-30%) | -0.0255 | -0.0352 | -0.2343 | -0.0593 | 0.2969 | 0.2484 | 1 | |
| Innovation** | (50%-50%) | -0.0396 | -0.0689 | -0.1937 | -0.0455 | 0.1518 | 0.1463 | 0.88 | 1 |

* based on patent counts

** based on percentage change in patent counts

Appendix 3: Monthly trend of various proxies for the European market portfolio




Appendix 4: Summary statistics of the variable raw patent counts

Table 12 : Summary Statistics of the variable raw patent counts

| | Observations | Mean | Median | Sd | Variance | Range | Min | Max |
|---|---|---|---|---|---|---|---|---|
| Austria | 18 | 531 | 545 | 153 | 23553 | 589 | 316 | 905 |
| Belgium | 18 | 646 | 693 | 149 | 22077 | 519 | 377 | 896 |
| Switserland | 18 | 1370 | 1390 | 185 | 34068 | 783 | 1106 | 1889 |
| Germany | 18 | 9870 | 10049 | 2045 | 4181860 | 6758 | 6875 | 13633 |
| Spain | 18 | 308 | 318 | 95 | 8971 | 324 | 168 | 492 |
| France | 18 | 3762 | 3809 | 596 | 354956 | 2116 | 2984 | 5100 |
| United Kingdom | 18 | 3681 | 3903 | 731 | 534398 | 2570 | 2468 | 5038 |
| Ireland | 18 | 141 | 154 | 62 | 3859 | 223 | 52 | 275 |
| Italy | 18 | 1754 | 1837 | 282 | 79477 | 1012 | 1242 | 2254 |
| Netherlands | 18 | 1374 | 1452 | 326 | 106243 | 1034 | 885 | 1919 |
| Aftermath | 30 | 2841 | 1554 | 3556 | 12600000 | 13446 | 187 | 13633 |
| Boom | 30 | 2460 | 1403 | 2965 | 8789194 | 10718 | 104 | 10822 |
| Crash | 40 | 2623 | 1545 | 3172 | 10100000 | 11807 | 147 | 11954 |
| Run-up | 80 | 1974 | 1188 | 2403 | 5774582 | 10837 | 52 | 10889 |
| Total | 180 | 2344 | 1386 | 2887 | 8336420 | 13581 | 52 | 13633 |

## Appendix 5: Composition of the portfolios

Table 13 : The composition of portfolios (based on raw patent counts)

| | | Total patents | Excess Return | Market premium | HML | SMB | %change in patents |
|---|---|---|---|---|---|---|---|
| Portfolios | Low | 141.0556 | 0.323 | 0.6849 | 0.4151 | -1028.0875 | 0.1048 |
| | | 307.7222 | 0.492 | 0.6890 | 0.4127 | -1028.1391 | 0.0805 |
| | | 527.6111 | 0.214 | 0.6858 | 0.4158 | -1028.0248 | 0.0519 |
| | | 649.3889 | 0.420 | 0.6864 | 0.4129 | -1028.1698 | 0.0638 |
| | | 1287.5556 | 0.560 | 0.6864 | 0.4174 | -1028.1165 | 0.0260 |
| | | 1456.6111 | 0.369 | 0.6867 | 0.4151 | -1028.0952 | 0.0533 |
| | | 1753.7778 | 0.042 | 0.6838 | 0.4173 | -1028.0326 | 0.0315 |
| | | 3586.8333 | 1.139 | 0.6917 | 0.4191 | -1028.1054 | 0.0386 |
| | | 3855.9444 | 1.091 | 0.6906 | 0.4186 | -1028.0523 | 0.0350 |
| | High | 9870.2222 | 0.516 | 0.6730 | 0.4029 | -1028.4439 | 0.0393 |
| Average | | 2343.6722 | 0.517 | 0.6858 | 0.4147 | -1028.1267 | 0.0525 |

Table 14 : The composition of portfolios (based on the percentage change in raw patent counts)

| | | %change in patents | Excess Return | Market premium | HML | SMB | Total patents |
|---|---|---|---|---|---|---|---|
| Portfolios | Low | -0.0641 | 0.033 | 0.6863 | 0.4187 | -1028.1933 | 1470.2778 |
| | | -0.0290 | 0.553 | 0.6878 | 0.4152 | -1028.1244 | 1453.6667 |
| | | -0.0026 | 0.134 | 0.6877 | 0.4129 | -1028.1776 | 2402.7222 |
| | | 0.0183 | 0.760 | 0.6882 | 0.4170 | -1028.1098 | 2776.6111 |
| | | 0.0299 | 1.021 | 0.6885 | 0.4170 | -1028.4013 | 3762.3889 |
| | | 0.0445 | 0.266 | 0.6873 | 0.4206 | -1027.9564 | 2785.0556 |
| | | 0.0632 | 0.567 | 0.6733 | 0.4016 | -1028.1384 | 3860.6111 |
| | | 0.0844 | 0.911 | 0.6853 | 0.4196 | -1027.8882 | 3128.2222 |
| | | 0.1476 | 0.459 | 0.6880 | 0.4125 | -1028.3054 | 1141.1111 |
| | High | 0.2323 | 0.589 | 0.6860 | 0.4119 | -1027.9721 | 656.0556 |
| Average | | 0.0525 | 0.529 | 0.6858 | 0.4147 | -1028.1267 | 2343.6722 |

Appendix 6: Summary statistics of the factor Innovation

Table 15 : Summary Statistics of the factor Innovation based on raw patent counts (50%-50%)

| | Observations | Mean | Median | Sd | Variance | Range | Min | Max |
|---|---|---|---|---|---|---|---|---|
| Aftermath | 46 | 2.9963 | 2.6072 | 2.6203 | 6.8657 | 8.8984 | -2.2001 | 6.6982 |
| Boom | 31 | 2.8317 | 1.6123 | 2.1563 | 4.6498 | 5.7622 | -0.5784 | 5.1838 |
| Crash | 48 | -0.7034 | -1.8763 | 3.5899 | 12.8874 | 11.1616 | -4.4634 | 6.6982 |
| Run-up | 91 | 0.7276 | 0.2306 | 1.4634 | 2.1414 | 4.4285 | -0.7667 | 3.6619 |
| Total | 216 | 1.1947 | 0.8862 | 2.7887 | 7.7770 | 11.1616 | -4.4634 | 6.6982 |

Table 16 : Summary Statistics of the factor Innovation based on raw patent counts (30%-30%)

| | Observations | Mean | Median | Sd | Variance | Range | Min | Max |
|---|---|---|---|---|---|---|---|---|
| Aftermath | 46 | 3.6540 | 3.0732 | 2.5496 | 6.5005 | 9.2024 | -2.3843 | 6.8181 |
| Boom | 31 | 3.1849 | 2.1092 | 1.6882 | 2.8502 | 4.1580 | 1.0746 | 5.2325 |
| Crash | 48 | -0.5757 | -0.6800 | 2.8649 | 8.2075 | 10.5358 | -3.7177 | 6.8181 |
| Run-up | 91 | 1.7330 | 2.2404 | 1.3910 | 1.9348 | 4.3810 | -0.3388 | 4.0422 |
| Total | 216 | 1.8374 | 2.1748 | 2.5758 | 6.6349 | 10.5358 | -3.7177 | 6.8181 |

Table 17 :Summary Statistics of the factor Innovation based on % change in raw patent counts(50%-50%)

| | Observations | Mean | Median | Sd | Variance | Range | Min | Max |
|---|---|---|---|---|---|---|---|---|
| Aftermath | 46 | 0.9922 | -0.1946 | 1.9550 | 3.8222 | 4.6159 | -1.4397 | 3.1762 |
| Boom | 31 | 1.2423 | -0.2148 | 2.4275 | 5.8928 | 6.8058 | -2.6429 | 4.1630 |
| Crash | 48 | 0.1965 | 0.0388 | 1.9076 | 3.6388 | 5.8191 | -2.6429 | 3.1762 |
| Run-up | 91 | -1.1261 | -0.3982 | 1.7930 | 3.2147 | 5.0711 | -4.0388 | 1.0323 |
| Total | 216 | -0.0412 | -0.2047 | 2.1772 | 4.7402 | 8.2018 | -4.0388 | 4.1630 |

Table 18 :Summary Statistics of the factor Innovation based on %change in raw patent counts(30%-30%)

| | Observations | Mean | Median | Sd | Variance | Range | Min | Max |
|---|---|---|---|---|---|---|---|---|
| Aftermath | 46 | 1.3596 | 0.2761 | 2.0838 | 4.3421 | 4.8407 | -1.0933 | 3.7473 |
| Boom | 31 | 1.3098 | 0.5529 | 1.4826 | 2.1982 | 4.8890 | -1.9847 | 2.9043 |
| Crash | 48 | 0.4725 | 0.9702 | 1.4308 | 2.0471 | 5.1303 | -1.9847 | 3.1457 |
| Run-up | 91 | -0.2714 | 0.5158 | 1.5274 | 2.3331 | 4.4773 | -2.5905 | 1.8867 |
| Total | 216 | 0.4682 | 0.5343 | 1.7730 | 3.1434 | 6.3379 | -2.5905 | 3.7473 |

Appendix 7: Results of the CAPM and the Fama French three-factor model on portfolios based on raw patent counts.

**Table 19: Results using the CAPM and the Fama French three-factor model**

*Dependent variable is the monthly excess return of around 3300 firms in the period of January 1993 until December 2010 within ten European countries, namely Austria, Belgium, France, Germany, Ireland, Italy, Netherlands, Spain, Switzerland and United Kingdom divided into ten portfolios. I trimmed the one percent highest and lowest observation of the dependent variable. Explanatory variables are the Fama and French three factors. The first (1) asset pricing model is the capital asset pricing model, the second (2) is the Fama French three-factor model. The stocks are formed into ten portfolios based on raw patent counts. Alpha is the intercept of the model. The t-statistics are in parentheses.*

| Portfolio | Observations | Excess Return | CAPM (1) | | | Fama French model (2) | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | | | Alpha | Market | Adj R-sq | Alpha | RMRF | SMB | HML | Adj R-sq |
| 1 (high) | 24695 | 0.323 | 0.224*** | 0.173*** | 0.030 | 1.800*** | 0.177*** | 0.00145*** | -0.0167 | 0.034 |
| | | | (4.78) | (27.66) | | (11.44) | (27.74) | (10.50) | (-1.14) | |
| 2 | 43230 | 0.492 | 0.364*** | 0.223*** | 0.061 | 1.619*** | 0.223*** | 0.00117*** | 0.0285** | 0.064 |
| | | | (11.60) | (52.81) | | (15.25) | (51.71) | (12.54) | (2.91) | |
| 3 | 33884 | 0.214 | 0.121*** | 0.143*** | 0.028 | 0.319** | 0.146*** | 0.00017 | -0.0376*** | 0.028 |
| | | | (3.41) | (31.12) | | (2.60) | (31.20) | (1.58) | (-3.51) | |
| 4 | 39439 | 0.420 | 0.324*** | 0.203*** | 0.050 | 1.191*** | 0.206*** | 0.000786*** | -0.0183 | 0.051 |
| | | | (9.93) | (45.52) | | (10.73) | (45.22) | (8.15) | (-1.75) | |
| 5 | 70212 | 0.560 | 0.415*** | 0.249*** | 0.073 | 0.948*** | 0.252*** | 0.000483*** | -0.0227** | 0.073 |
| | | | (16.44) | (74.18) | | (10.93) | (73.42) | (6.37) | (-2.89) | |
| 6 | 64783 | 0.369 | 0.237*** | 0.229*** | 0.058 | 0.900*** | 0.230*** | 0.000619*** | -0.0047 | 0.059 |
| | | | (8.96) | (63.12) | | (10.20) | (62.24) | (7.89) | (-0.56) | |
| 7 | 79601 | 0.042 | -0.101*** | 0.260*** | 0.079 | 0.405*** | 0.261*** | 0.000465*** | 0.000591 | 0.079 |
| | | | (-4.26) | (82.63) | | (4.99) | (81.06) | (6.55) | (0.08) | |
| 8 | 67740 | 1.139 | 0.897*** | 0.442*** | 0.135 | 1.019*** | 0.441*** | 0.00013 | 0.00737 | 0.135 |
| | | | (31.00) | (102.71) | | (10.42) | (101.73) | (1.34) | (0.78) | |
| 9 | 51906 | 1.091 | 0.810*** | 0.409*** | 0.170 | 2.467*** | 0.412*** | 0.00136*** | -0.00621 | 0.173 |
| | | | (24.90) | (103.18) | | (19.80) | (100.05) | (13.82) | (-0.63) | |
| 10 (low) | 41300 | 0.516 | 0.386*** | 0.422*** | 0.131 | 1.409*** | 0.433*** | 0.000841*** | -0.0880*** | 0.133 |
| | | | (8.85) | (78.98) | | (7.77) | (78.67) | (5.66) | (-6.83) | |

t statistics in parentheses

* $p<0.05$, ** $p<0.01$, *** $p<0.001$

Appendix 8: Results of Fama French three-factor model on portfolios based on raw patent counts and on percentage change in patents using raw dataset.

## Table 20: Pricing of the innovation factor using raw dataset

*Dependent variable is the monthly excess return of around 3300 firms in the period of January 1993 until December 2010 within ten European countries, namely Austria, Belgium, France, Germany, Ireland, Italy, Netherlands, Spain, Switzerland and United Kingdom divided into ten portfolios.. Explanatory variables are the Fama and French three factors and an innovation factor. The table reports the estimates of the Fama French three-factor model. First (1), the stocks are formed into ten portfolios based on raw patent counts. In the second case (2), I used percentage change in patent counts to form the portfolios. Alpha is the intercept of the model. The t-statistics are in parentheses.*

| Portfolio | Observations (1) | Observations (2) | Excess Return (1) | Excess Return (2) | Fama French model (1) | | | | | Fama French model (2) | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | | | | Alpha | Market | SMB | HML | Adj R-sq | Alpha | Market | SMB | HML | Adj R-sq |
| 1 (high) | 24695 | 49902 | 0.769 | 0.105 | 2.869*** | 0.286*** | 0.00208*** | -0.00892 | 0.025 | 1.113*** | 0.394*** | 0.000862*** | -0.0158 | 0.063 |
| | | | | | (9.55) | (23.52) | (7.91) | (-0.32) | | (5.70) | (56.21) | (5.14) | (-0.96) | |
| 2 | 43230 | 47841 | 0.853 | 1.179 | 2.478*** | 0.292*** | 0.00168*** | 0.0490** | 0.033 | 2.401* | 0.297*** | 0.00146 | 0.0526 | 0.001 |
| | | | | | (12.48) | (36.25) | (9.59) | (2.67) | | (2.27) | (6.69) | (1.51) | (0.55) | |
| 3 | 33884 | 59920 | 0.721 | 0.336 | 0.856* | 0.238*** | 0.000255 | -0.037 | 0.009 | 0.774** | 0.457*** | 0.000522* | -0.0399* | 0.049 |
| | | | | | (2.40) | (17.43) | (0.81) | (-1.19) | | (3.25) | (54.77) | (2.51) | (-2.08) | |
| 4 | 39439 | 54471 | 0.708 | 1.348 | 1.431*** | 0.267*** | 0.000772*** | -0.00383 | 0.026 | 2.122*** | 0.454*** | 0.00103* | 0.107 | 0.006 |
| | | | | | (7.02) | (31.90) | (4.36) | (-0.20) | | (3.92) | (17.25) | (2.09) | (1.89) | |
| 5 | 70212 | 50854 | 1.060 | 1.354 | 0.883 | 0.300*** | 0.0000334 | 0.0974 | 0.003 | 2.511*** | 0.453*** | 0.00130*** | 0.0243 | 0.085 |
| | | | | | (1.46) | (12.57) | (0.06) | (1.78) | | (13.14) | (67.29) | (8.18) | (1.52) | |
| 6 | 64783 | 51384 | 0.877 | 0.430 | 2.111* | 0.331*** | 0.00133 | 0.00319 | 0.002 | 2.216*** | 0.458*** | 0.00164*** | -0.0862*** | 0.086 |
| | | | | | (2.56) | (9.58) | (1.82) | (0.04) | | (11.39) | (67.81) | (10.29) | (-5.02) | |
| 7 | 79601 | 53091 | 0.367 | 3.844 | 0.764*** | 0.355*** | 0.000555*** | 0.0359** | 0.052 | 9.373 | 0.377 | 0.00492 | -1.195 | 0.000 |
| | | | | | (5.47) | (64.19) | (4.56) | (2.82) | | (1.04) | (1.04) | (0.61) | (-1.42) | |
| 8 | 67740 | 61364 | 1.485 | 1.566 | 1.211** | 0.518*** | 0.0000377 | 0.0578 | 0.013 | -0.253 | 0.380*** | -0.00141** | 0.140** | 0.006 |
| | | | | | (3.10) | (29.86) | (0.10) | (1.52 | | (-0.43) | (17.10) | (-2.65) | (2.91) | |
| 9 | 51906 | 47900 | 1.272 | 0.730 | 3.129*** | 0.571*** | 0.00186*** | 0.0556*** | 0.157 | 1.962*** | 0.302*** | 0.00132*** | 0.0353 | 0.024 |
| | | | | | (16.83) | (92.98) | (12.67) | (3.78) | | (9.16) | (32.52) | (7.26) | (1.66) | |
| 10 (low) | 41300 | 40063 | 4.477 | 0.971 | 21.3 | 0.733 | 0.0139 | -1.583 | 0.000 | 1.953*** | 0.332*** | 0.00120*** | 0.0274 | 0.027 |
| | | | | | (1.45) | (1.65) | (1.16) | (-1.52) | | (8.85) | (32.38) | (6.20) | (1.18) | |

t statistics in parentheses

* $p<0.05$, ** $p<0.01$, *** $p<0.001$