Aalto University
School of Business

Manufacturing and the q-factor pricing model

Assessing the difference between the q-factors constructed from manufacturing and non-manufacturing stocks

Master's Thesis
Michaela Svobodova
Aalto University School of Business
Master's Programme in Finance
Spring 2021

Aalto University
School of Business

Author Michaela Svobodova

Title of thesis Manufacturing and the q-factor pricing model

Programme Master's Programme in Finance

Major Finance

Thesis supervisor Prof. Matti Suominen

Thesis advisor(s)

Date 30.07.2021 **Number of pages** 73 **Language** English

Abstract

This thesis looks at the differences between the q-factor asset pricing model (Hou, Xue, and Zhang, 2015) factors constructed from manufacturing sector stocks and the factors created from the non-manufacturing stocks. The differences between the corresponding factors were tested with the paired sample t-test. The differences between the market, the size, and the investment factors were not found to be statistically significant at any reasonable level, neither in the shorter sample 1992-2019, nor in the longer period 1967-2019, which was used as a robustness check. The profitability factor created from the manufacturing stocks had on average lower returns than that created from the non-manufacturing stocks. This difference was statistically significant at 5% level in the short sample, but it was not significant during the longer sample period.

Keywords Q-factor model, Asset pricing model, Stock pricing, Manufacturing, Investment factor, Profitability factor

Table of Content

Preface

I would like to thank my thesis supervisor, Matti Suominen, for guiding me when I got stuck and Sean Shin for helping me find errors in my methodology.

I would also like to thank my family and friends for striking the perfect balance between being supportive and pushy. It was not always appreciated, but it is now.

Symbols and abbreviations

Symbols

<=>	Equivalent

Abbreviations

CCMA	CRSP/Compustat Merged - Fundamentals Annual database
CCMQ	CRSP/Compustat Merged - Fundamentals Quarterly database
CRSP	Center for research in Security prices database
FF	Fama-French
FF3	Fama-French three-factor model
FF4	Fama-French four-factor model
FF5	Fama-French five-factor model
FF6	Fama-French six-factor model
HML	Fama-French value factor
HMXZ	Hou, Mo, Xue, and Zhang
HXZ	Hou, Xue, and Zhang
I/A	Investment
I/A factor	Investment factor
ME	Size
ME factor	Size factor from q-factor model
q-factors	q-factor model factors, i.e. market, size, investment, and profitability factor
ROE	Profitability, more precisely return on equity
ROE factor	Profitability factor
SMB	Fama-French size factor
_H	Hou, Xue, and Zhang
_m	manufacturing stocks
_nm	non-manufacturing stocks

1 Introduction

The q-factor model proposed by Hou, Xue, and Zhang (2012) is one of the most recent asset pricing models and is a serious contender to be the benchmark asset pricing model. It is composed of four factors, market excess return factor, size factor, investment factor, and profitability factor ("q-factors"). Despite its surge in popularity over the recent years, there are still research questions related to the q-factor model that are yet to be tested. One interesting question that is addressed in this paper is whether the q-factor model works better in the manufacturing sector.

More precisely, this thesis aims to assess the difference between the returns on the q-factors created from stocks of manufacturing companies and the q-factors constructed from the rest of the economy. This will show in what areas is the manufacturing sector the same as the rest of the economy, and perhaps more interestingly, where it deviates.

One supposition is that the q-factor model, whose theoretical backing relates the firm's investment and profitability to its cost of capital, might work better in manufacturing where the firms' financing needs vary significantly across firms. On the other hand, manufacturing is well understood business and therefore the financing frictions and consequently entry barriers in that sector could be smaller, and due to this the cost of capital might also be lower. How well the q-factor model works in the manufacturing sector as opposed to other sectors is therefore an empirical matter. However, there is some theory, which is introduced below, that provides a backing to the investment factor and profitability factor hypotheses, despite the fact that there seem to be possibly opposing intuitive motivations for the size of returns on the manufacturing q-factors.

The US manufacturing sector accounts for the largest part of the listed US companies among all the sectors. It has historically been the backbone of the US economy and plays a crucial role to date. As such, the manufacturing sector deserves to be paid special attention. Not to mention that due to its steady influence on the US economy and number of listed companies pertaining to it, it is the only sector for which the q-factors can be constructed, while maintaining a reasonable size of the underlying portfolios.

Seeing if the factors behave the same for all parts of the economy could also have practical implications. Uncovering higher returns on the q-factors created from the manufacturing sector could potentially lead to discovery of a more profitable investments and higher returns on investments.

Even though the q-factor model is competing well with the other asset pricing models, there are still more commonly used asset pricing models. Prime examples are CAPM (Markowitz, 1952) and Fama-French ("FF") three-factor model (Fama-French, 1992). Fama-French in particular do not seem to want to lose out to Hou, Xue, and Zhang, which has led them to add factors resembling Hou, Xue, and Zhang's investment and profitability factors to their three-factor model.

The idea of including the investment and profitability factors in asset pricing models is clearly gaining traction. However, as was already mentioned, an assessment of these factors against a subset of US economy, such as the manufacturing sector, has not been carried out yet. Fortunately, there are some relevant theoretical papers aiding in creation of hypotheses for the manufacturing q-factors. Fernando and Mulier (2015) link the firm's leverage to its financial constraints in their paper. Hou, Xue, and Zhang (2015) then in turn explain the relation of the financial constraints to the investment variable and the profitability variable. Based on these links and observations regarding the leverage of manufacturing firms, the investment factor and profitability factor hypotheses are created.

The investment factor hypothesis states that the manufacturing investment factor will be higher than the one constructed from the non-manufacturing stocks. The hypothesis is created based on Fernando and Mulier (2015) paper which showed the positive correlation between leverage and financial constraints. In turn Hou, Xue, and Zhang (2015) assert that firms with lower discount rates have higher investment and vice versa. Lastly, table 4 of Bernanke et al. (1990) shows that the range of debt-to-asset ratio is wider for the manufacturing sector industries than it is for the other sectors. These observations give rise to the investment factor hypothesis

The profitability factor hypothesis in turn asserts that the manufacturing profitability factor will be lower than the factor created from the rest of the economy. This hypothesis is created based on the fact that the leverage and profitability are positively correlated (Baker, 1973) and the manufacturing sector has historically had significantly lower leverage than the rest of the economy. The hypothesis is also based on empirical observations from Ready Ratios ([45]), which shows that the differences in the gross profit margin medians are lower for the manufacturing sector industries than the rest of the industries.

The results presented in this paper provide some evidence that manufacturing sector is indeed different from the rest of the economy. Regrettably, the evidence is quite weak. The most noteworthy result presented in this paper is the result for the profitability factor. The findings suggest that the returns on the manufacturing profitability factor are significantly lower than the returns on non-manufacturing profitability factor. That is in line with the profitability factor hypothesis devised herein. However, these results are undercut by the fact that in the longer sample period, which serves as a robustness check, the difference between the returns on the profitability factors is not statistically significant.

The findings related to the other q-factors are less interesting, due to the lack of statistical significance. The results for the investment factor have the same direction as is expected in the hypothesis, i.e., the manufacturing investment factor has higher returns. However, the difference between the returns on manufacturing and non-manufacturing investment factor is not statistically significant in the sample period. So even though the difference approaches statistical significance in the longer sample period, which is used as a robustness check, the investment factor hypothesis is rejected.

The findings for the market factor and the size factor are the least interesting, as the manufacturing market and size factors do not significantly differ from their non-manufacturing counterparts.

The contribution of this paper comes then mainly from uncovering the potential relationship between the manufacturing sector and the profitability factor. However, since the evidence for this is limited, further research to this topic will have to be carry out to affirm whether profitability factor created from manufacturing stocks indeed brings lower returns.

In part two of this thesis, following the introduction, is the literature review. The first section of this part deals with the history of stock pricing models. The following section deals with the q-factor model. First subsection of the q-factor model section is devoted to a general model overview. The following subsections are dealing with the theoretical backing of the four factors, i.e., the market excess return factor, the size factor, the investment factor, and the profitability factor. The last section of the literature review then deals with the manufacturing sector, mainly in terms of the theoretical ties of the manufacturing sector to the four q-factors' returns. The hypotheses are presented at the end of this section.

Part three of this thesis outlines the data and methodology employed. The data discussion is broken down by the different databases. Following that is the description of the methodology used. The methodology is fully explained, starting with the cleanup of the data, continuing with the variable creation and assignment into groups, and ending with factor creation.

After the methodology section come the results, which are laid out in part four. In the first section of this part is the comparison between the results obtained by employing the methodology outlined in part three and the data provided by Hou, Mo, Xue, and Zhang (2020b). This is done to check whether the methodology used resembles the methodology employed by Hou, Xue, and Zhang (2015) closely enough. After this sanity check, the properties of the factors constructed from the US manufacturing stocks are presented. For each factor the main statistics of returns, the correlations and paired sample t-tests of the manufacturing factors and the non-manufacturing factors are presented. The paired sample t-tests are then used to validate the hypotheses.

The penultimate, fifth, part of this thesis is dedicated to the discussion of the results. The main goal of this part is to discuss the robustness and validity of the findings presented in the results part. This is then followed by the last part, the conclusion. This sums up the main findings, their impact, their robustness, and provides a few ideas for potential further research topics.

2 Literature review

2.1 Stock pricing models history

Since the introduction of the capital asset pricing model ("CAPM"), which is jointly ascribed to Markowitz (1952), Treynor (1961), Sharpe (1964), Lintner (1965), and Mossin (1966), the race to find anomalies and factors that would render these anomalies insignificant has been underway.

Under the capital asset pricing model, the stock returns are dependent on loading on a single risk factor. In CAPM, the stock excess return, i.e. the return of the stock minus the risk free rate, depends on market excess return factor. The derivation of CAPM is shown in subsection 2.2.2.

However, the era of single risk factor model is now quite undeniably over. In the literature there are now hundreds of anomalies and number of multi-factor models that are competing for the spotlight. Among the most notable ones are Fama-French ("FF") (1992), Carhart (1997), and Hou, Xue, and Zhang ("HXZ") (2015) models.

The Fama-French (1992) and Fama-French (1993) three-factor model ("FF3") is one of the earliest and most widely spread models. This model introduced the size ("SMB") and value ("HML") factor as an addition to the original market risk premium factor. The size factor is based on the size effect shown by Banz (1981), who demonstrated that smaller-cap stocks have higher returns than bigger cap stocks. The value factor comes from the insight presented by Stattman (1980) and Rosenberg, Reid, and Lanstein (1985), who found that stock returns are positively correlated the book-to-market ratio, meaning that high book-to-market stocks, i.e., value stocks, outperform low book-to-market stocks, i.e., growth stocks.

The Fama-French three-factor model is widely popular and has been cited over 20,000 times. However, as is true of most finance concept, no model is infallible and even FF3, despite its wide popularity, has its limits. The anomalies literature pointing out shortcomings in the FF3 model gave rise to other multi-factor asset pricing models.

One of the most prevalent anomalies groups was the momentum anomalies group (as shown e.g., in Jagadeesh and Titman, 1993). Momentum is the observed tendency of stocks with strong past performance to continue outperforming stocks with poor past performance in the following period. This Fama-French three-factor model's shortcoming with regards to momentum was tackled by Carhart (1997) four-factor model, which added a one-year momentum factor to the FF3. The momentum factor takes the previous winners (firms with the highest 11 month returns lagged by one month) and subtracts the losers (firms with the lowest 11 month returns lagged by one month).

Hou, Xue, and Zhang (2015) also pointed out faults in FF3 and as an alternative offered their q-factor asset pricing model, which is the focus of this thesis. The factors proposed are the market excess return factor, size ("ME") factor, investment ("I/A") factor, and profitability ("ROE") factor. In their sample of nearly 80 variables, containing all major categories of anomalies, HXZ tested the performance of their q-factor model against FF3 and Carhart model. In the test the q-factor model outperformed both the FF3 and the Carhart model. The average magnitude of alphas for the q-factor model was only 0.20%, compared to 0.33% for Carhart model and 0.55% for FF3. Similarly, only 5 of the alphas were significant for the q-factor model, which was less than a fourth that of Carhart model and fifth that of FF3.

Interestingly, the introduction of the profitability factor in HXZ (2015) was not the first time profitability was considered as a pricing factor. Novy-Marx (2013) has already put forth profitability as a good predictor of cross-section of average returns. The article was submitted in 2011. However, in contrast to HXZ (2015), Novy-Marx (2013) did not offer a theoretical backing and the construction of the factor was based on gross profit-to-assets, rather than return on equity, as in the q-factor model.

The biggest competition of the q-factor model seem to be the models proposed by Fama-French. That is probably why HXZ (2015) clarify the chronology of the new factor introduction in one of their footnotes. The first draft of the HXZ (2015) paper was dated October 2012. Fama-French shortly thereafter came with two papers Fama-French (2013) and Fama-French (2014), introducing their four-factor pricing model and five-factor pricing model, respectively (HXZ, 2015, p.4). The 2013 draft adds profitability factor to the FF3 and the 2014 draft adds investment factor on top of that. The Fama-French five-factor model ("FF5") was then published in 2015.

In their paper FF (2015) acknowledge the q-factor model (HXZ, 2012) as the model closest related to theirs and state that the factors examined by HXZ are largely similar to their own, with the exception of their HML factor (the value factor). FF (2015) note, that the HXZ (2012) makes no comment as to why HML factor was omitted and that the comparison of the q-factor is made only to the CAPM, FF3 and Carhart models. They argue that the analysis conducted by HXZ is more restricted than their own and that alternative factor definitions are not considered in HXZ paper. However, FF do not provide any further information as to what the particular difference in breath of the analyses concluded by themselves as opposed to HXZ is, nor do they state concretely what additional types of anomalies HXZ (2015) omits to analyse. The only relatively more concrete objection they raise against the HXZ (2012) approach is that they principally focus on explaining anomalies constructed from value-weighted portfolios from univariate sorts on variables. The issue FF (2015) take with this approach is that the value-weighted portfolios constructed this way are typically dominated by larger stocks, while the most significant issues of asset pricing stem from small stocks.

HXZ (2014, 2017a) also compare the FF5 to their q-factor model, both theoretically and empirically. In their comparison they argue that FF5 investment and profitability variables lack proper motivation and theoretical backing and that the HML factor seems redundant. Empirically they also conclude that their model is superior to the FF5.

Contrary to the FF (2015) claims, they deduce that the testing portfolios added by FF (2016) are just a subset of HXZ (2015) universe of nearly 80 anomalies, implying that HXZ analysis is more extensive.

The HXZ (2017a) tests the model on a data library of 437 anomaly variables, out of which 161 are significant when NYSE breakpoints are used and microcaps are controlled for and 216 are significant with all-but-micro breakpoints and equal-weighted returns. With t-statistics of 3, as suggested by Harvey, Liu, and Zhu (2016), 66 and 120 anomalies are still significant, respectively. Controlling for microcaps, i.e., by definition given in HXZ (2016, p. 1) stocks of companies with capitalization below the 20^{th} percentile at NYSE, renders most of the explored anomalies insignificant. This supports the FF (2015) claim, that most anomalies stem from small stocks.

When comparing the pricing models, HXZ (2017a) determine that the average alphas are roughly 40% higher for the FF5 than the q-factor model and over 80% more alphas are significant under FF5 than under the q-factor model. HXZ conclude that the FF5 profitability and investment factors are just noisy versions of the q-factor model profitability and investment factors.

Similarly to HXZ (2015), Stambaugh and Yuan (2017) also take the market factor and size factor and add two more factors in their model construction. These new factors are so called "mispricing" factors. Their approach in constructing the new factors is novel in that these factors are not created based on one anomaly, but multiple anomalies. They create the two factors from 11 prominent anomalies. Among these anomalies are investment-to-assets and profitability factors. The anomalies are grouped based on their correlation and then the mispricing factors are created based on these groups. By averaging rating on multiple anomalies, they attempt to reduce the noise in measures of stocks' mispricing. The motivation of these new factors is that they partially reflect mispricing and possess common sentiment effects.

Stambaugh and Yuan (2017) conclude that their model's ability to absorb anomalies exceed HXZ (2015) q-factor model and FF5 model. They make this conclusion based on set of 73 anomalies, which was examined by HXZ (2015). That is, however, not the same conclusion that Hou, Xue, and Zhang (2018) come to. HXZ conclude that both models perform comparably well.

Barillas and Shanken (2018) also attempt to find the best asset pricing model, but they do so by looking at factors from existing models, not adding their own. They take the factors proposed by FF5 and q-factor model, as well as Carhart's (1997) UMD factor, and Asness' and Fazzini's (2013) HML^m factor, which is a value factor alternative to FF3 model's HML factor. That means their factor space consists of 4 pairs of comparable factors with similar construction (investment, profitability, size, and value factors) plus market factor and UMD factor. By employing a test procedure they developed they conclude that the best model includes the market factor, UMD factor, FF's SMB factor, q-factor's I/A and ROE factors and Asness' and Fazzini's (2013) HML^m factor.

In 2018 Fama-French added a momentum factor to their FF5 model, creating a six-factor model ("FF6"), in order to "*satisfy insistent popular demand*" (FF 2018, p.237). However, they simultaneously voice their concerns around the lack of theoretical backing of the newly added factor and possible effect on the playing field, where theoretical backing will give way to seemingly empirically robust models. They fear the comparison between the asset pricing models will become unattainable due to the large (and ever growing) number of contenders.

In the paper FF (2018) mainly discuss the metrics used to evaluate the valuation models. The most prevalent approach employed by FF, HXZ and Stambaugh and Yuan (2017), which FF (2018) calls the "left-hand-side approach", is evaluating the abnormal returns, i.e., the intercept in regressing the given anomaly on the model's factors. An alternative evaluation approach, denoted as "right-hand-side approach", is to use spanning test to see if a factor contributes to model's explanatory power. According to FF (2018), the right-hand-side approach helps choose the best fitting model among the nested models.

FF (2018) also propose, that since the playing-field of the asset pricing model is growing exponentially, the range of competing models should be limited. The proposed limiting factors are two. The first is theory backing of the factors, by which they mean that factors should have at least an "umbrella theory", for that they give HXZ (2015) as example. The second proposed hurdle is the factor's performance out-of-sample. For all the talk of comparing the models Fama-French (2018) do not attempt to gauge whether their FF6 model is superior to the other therein-mentioned models or not.

Daniel, Hirshleifer, and Sun (2020) also "threw their hat in the ring", introducing two new factors in addition to the traditional market factor. The two new factors are theory-based behavioural factors. These factors aim to capture short-horizon and long-horizon mispricing and are motivated "*based on different forms of mispricing*", where "*[b]ehavioral theories suggest distinct mispricing mechanisms that will correct at shorter or longer horizons*" (Daniel, Hirshleifer, and Sun, 2020, p. 1674). However, the motivation does not come with a mathematical model. This puts the model in disadvantage compared to the q-factor model, at least when it comes to theoretical backing.

Hou, Mo, Xue, and Zhang are also continuously striving to make improvements to their q-factor model to stay competitive in the light of all the new competitors for the honour of creating the benchmark asset pricing model. To that end HMXZ (2017, 2018) have augmented their q-factor model by adding an expected growth factor. They dubbed this the q^5 model. The expected growth factor is different to the factors proposed by HXZ previously. It is constructed using cross-sectional growth forecasts with Tobin's q, operating cash flows, and change in return on equity as predictors. They conclude that adding the expected growth factor improves their model's performance "*across most anomaly categories, especially in the investment and profitability categories*" (HMXZ 2020, p. 3).

HXMZ (2018, 2019, 2020a) have also tested their q-factor model and q^5 model against other recently proposed models, namely FF5, Stamaugh and Yuan (2017) model, FF6, Barillas and Shanken (2018) model, and Daniel, Hirshleifer, and Sun (2020) model. They determined, that the q^5 model is superior to all the others. Already the q-factor fares well against the FF6, having slightly lower average alpha and fewer significant alphas, but the Gibbons Ross Shanken (1989) (GRS) test has fewer rejections for FF6 compared to q-factor model. The q-factor model is also comparable to the Stamaugh and Yuan (2017) model and it performs significantly better than Barillas and Shanken (2018) model, and Daniel, Hirshleifer, and Sun (2020) model. In their analysis HMXZ (218, 2019, 2020a) show that the q^5 model outperforms all the other studied models.

HMXZ (2018) conclude, based on a spanning test, that FF5 and FF6 are just noisy versions of q-factor model and q^5 model. They also conclude that the "mispricing" factors from the Stambaugh and Yuan (2017) are close to the q-factors with correlation over 0.8 and Stambaugh and Yuan (2017) "*statistical cluster analysis essentially rediscovers the q-factors*" (HMXZ, 2018, p.3).

Hou, Xue, and Zhang provide a compelling theoretical reasoning and empirical evidence supporting the superiority of their models. However, that should not be taken as an endorsement of one asset pricing model over the others as no attempt has been made herein to carry out an impartial comparison.

Furthermore, the overview presented above is by no means an exhaustive recapitulation of all existing asset pricing models. The asset pricing models literature and the anomalies literature are much more vast than could be recounted herein. The overview serves more as an introduction of the main contenders for the most precise model. These were selected chiefly based on mentions by reputable sources, so mostly by either the FF or the HXZ papers. As for the models' performance and their ranking, these are quite dependent on the data and anomalies selected as the playing field and the tests carried out for the comparison. This can be seen also by different authors claiming the superiority of their model based on different metrics.

The q-factor model was chosen as the backbone of this thesis because it is newer than the Fama-French models and Hou, Xue, and Zhang make compelling arguments as to why their model is superior. Furthermore, the lack of literature examining the difference in profitability and investment in the manufacturing sector offers an interesting area of exploration for this thesis.

2.2 Q-factor model

In this section the q-factor model developed by Hou, Xue, and Zhang (2015), which was shortly introduced in section 2.1, is discussed in more detail. First the model is introduced and then the theoretical backing of its factors, i.e., market, size, investment, and profitability factor, is examined.

2.2.1 Q-factor model overview

The HXZ q-factor model, as introduced in the section 2.1, is an "*empirical model that largely summarizes the cross section of average stock returns*" (HXZ, 2015, p.651). They specify the model as follows,

$$E[r_i] - r_f = \beta^i_{MKT} E[r_{MKT}] + \beta^i_{ME} E[r_{ME}] + \beta^i_{I/A} E[r_{I/A}] + \beta^i_{ROE} E[r_{ROE}] \quad . \tag{1}$$

The expected excess return on the asset, i.e., $E[r_i] - r_f$, is thus explained by the sensitivities to the four following factors:

- r_{MKT} - market excess return,
- r_{ME} – difference between returns on small and big stocks portfolios,
- $r_{I/A}$ – difference between returns on low and high investment stocks portfolios, and
- r_{ROE} – difference between returns on high and low profitability stocks portfolios.

The $E[factor]$ and β^i_{factor} in equation (1) correspond to expected factor premium and factor loading, respectively.

In the sections below, each factor's theoretical backing is discussed. This includes a short literature review as well as mathematical model derivation. This is, namely, CAPM for the market factor, Berk et al. (1999) model for the size factor, and HXZ (2015) two-period stochastic general equilibrium model for investment and profitability factor.

2.2.2 Market factor theory

The theoretical backing and construction of the market factor is not closely described in the HXZ (2012) paper. However, it is clear that HXZ, similarly to FF, draw from the capital asset pricing model. The mathematical derivation is carried out below, after the discussion of CAPM assumptions and the graphical visualization of CAPM.

CAPM has a few very strong assumptions about the investment world. The strength of these assumptions and their unfeasibility in real life is likely why there are so many contestants to surpass it. Nevertheless, it is impossible to test for whether the assumptions hold, because any test of the market efficiency is also jointly a test of the selected market equilibrium model (Fama, 1970).

The first assumption is about investor behaviour. Under this condition, the investors are risk-averse, rational, and when choosing a portfolio, they care only about the mean and variance of their one-period returns. This leads to investors seeking portfolio with highest return given variance and vice versa, i.e., "mean-variance-efficient" portfolio.

The next two assumptions are about the investment universe. The second CAPM assumption states that investors choose where to allocate their assets in one period prior to payoff. The third assumption is that the investors can lend and borrow money at the risk-free rate.

The last assumption asserts that there are no taxes, inflation, and that the world is frictionless, i.e., there are no transaction costs. The capital asset pricing model is built on these four assumptions.

The graphical representation of CAPM and the investment opportunities in the CAPM universe is shown in Figure 1. It has standard deviation as a measure of risk (σ) on x-axis and expected return as portfolio return ($E(r)$) on y-axis.

The tangency portfolio (T) lies on intersection of the minimum variance frontier (i.e., efficiency frontier) and the tangency line from the risk-free rate (r_f), i.e., the mean variance-efficient frontier with riskless asset (i.e., the capital market line). It is an optimal risky portfolio w.r.t. risk and return trade-off. The tangency portfolio must be a market portfolio, otherwise the market would not clear. Each investor then chooses to hold market portfolio and riskless asset (Fama-French, 2004).

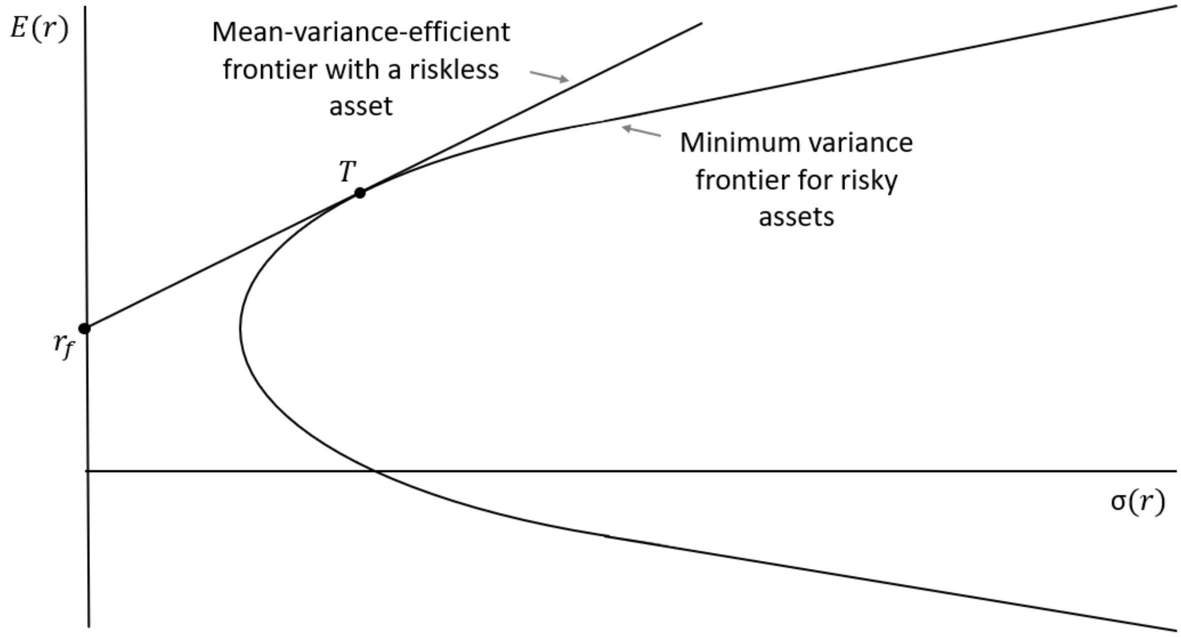

Figure 1 - CAPM investment opportunities

The mathematical derivation of CAPM is presented hereunder (Suominen, 2019). Assuming that part of investor's portfolio *p* is invested in a risky asset *i* and the rest is invested in the market portfolio *m*. This leads to the following expected portfolio return and risk,

$$E(r_P) = \alpha E(r_i) + (1-\alpha)E(r_m) \quad , \tag{2}$$

and

$$\sigma(r_P) = \sqrt{\alpha^2\sigma_i^2 + (1-\alpha)^2\sigma_m^2 + 2\alpha(1-\alpha)\sigma_{im}} \quad . \tag{3}$$

The $E(r)$stands for the expected return, the σ^2 is the variance, the σ_{im} is the covariance between the risky asset and the market portfolio, and α is a constant showing how much of the investor's portfolio is allocated in the risky asset.

Therefore, the return-risk trade-off (i.e., how much does the expected return change relative to change of risk when weights are adjusted) of this portfolio is

$$\frac{dE(r_P)}{d\sigma(r_P)} = \frac{\frac{\partial E(r_P)}{\partial \alpha}}{\frac{\partial \sigma(r_P)}{\partial \alpha}} = \frac{E(r_i) - E(r_m)}{\left(\frac{\alpha\sigma_i^2 - (1-\alpha)^2\sigma_m^2 + \alpha(1-2\alpha)\sigma_{im}}{\sqrt{\alpha^2\sigma_i^2 + (1-\alpha)^2\sigma_m^2 + 2\alpha(1-\alpha)\sigma_{im}}}\right)} \quad . \tag{4}$$

When $\alpha = 0$, then $E(r_P) = E(r_m)$ and $\sigma(r_P) = \sigma(r_m)$. The curve therefore touches the capital market line at the market point $(\sigma(r_m), E(r_m))$. Since the curve is tangent to asset line at the market point, the curve's derivative at $\alpha = 0$ equals the slope of the capital asset line at the market portfolio point (Sigman, 2005)

$$\left.\frac{dE(r_P)}{d\sigma(r_P)}\right|_{\alpha=0} = \frac{E(r_m) - r_f}{\sigma_m} \quad . \tag{5}$$

Evaluating the expression in equation (4) at $\alpha = 0$, yields

$$\left.\frac{dE(r_P)}{d\sigma(r_P)}\right|_{\alpha=0} = \frac{E(r_i) - E(r_m)}{\frac{\sigma_{im} - \sigma_m^2}{\sigma_m}} \quad . \tag{6}$$

Plugging the expression (6) into the equilibrium equation (5) results in the capital asset pricing model

$$\frac{E(r_i) - E(r_m)}{\frac{\sigma_{im} - \sigma_m^2}{\sigma_m}} = \frac{E(r_m) - r_f}{\sigma_m} \quad . \tag{7}$$

Expressing the abnormal asset returns from equation (7) results in

$$E(r_i) - r_f = \frac{\sigma_{im}}{\sigma_m^2}\left(E(r_m) - r_f\right) \quad . \tag{8}$$

By defining the price of risk of asset *i* as $\beta_i = \frac{\sigma_{im}}{\sigma_m^2}$, CAPM can be expressed as

$$E(r_i) - r_f = \beta_i\left(E(r_m) - r_f\right) \quad . \tag{9}$$

Equation (9) shows that stock excess return, i.e. the return of the stock minus the risk free rate, is dependent on market risk loading and market excess return. The latter is the definition of the market factor.

2.2.3 Size factor theory

Similarly to the market factor, the theoretical backing for the size factor is not closely examined by HXZ (2012) either. Since Hou, Xue, and Zhang compare their model performance to Fama-French models, it is likely that the FF size factor is an inspiration for the HXZ size factor.

FF do not offer mathematical derivation of the size factor. Instead they base their reasoning for adding the size factor on the fact that the phenomenon of smaller stocks offering a premium return over stocks of companies with larger market capitalization is a well-documented one.

The so-called size effect was first observed by Banz (1981), who used it to argue that CAPM is misspecified. As to the theoretical backing of this phenomenon, Banz asserted that there is no theoretical foundation for such effect and that it was unknown whether the size itself is the factor, or it is just a proxy for some other factor. However, he put forth an informal model explaining the rationale behind the size effect. This rationale is based on a model by Klein and Bawa (1977): *"[I]f insufficient information is available about a subset of securities, investors will not hold these securities because of estimation risk, i.e., uncertainty about the true parameters of the return distribution. If investors differ in the amount of information available, they will limit their diversification to different subsets of all securities in the market. It is likely that the amount of information generated is related to the size of the firm. Therefore, many investors would not desire to hold the common stock of very small firms. [...] Thus, lack of information about small firms leads to limited diversification and therefore to higher returns for the 'undesirable' stocks of small firms"* (Banz, 1981, p.17). This intuitive explanation thus ties the size of stocks to its returns via information asymmetry. However, it comes with a caveat that although this explanation is consistent with the empirical results, it is still just an unproven conjecture.

Building on Banz's (1981) proxy idea, FF (1992) assert that size can be regarded as a way "*to scale stock prices, to extract the information in prices about risk and expected returns*" (FF, 1992, p.428). They argue, that stock risks are multidimensional and size is a proxy of one of the dimensions of risk.

FF (1992) also observe a negative correlation between the size and book-to-market equity variable, concluding that part of the size effect is due to small stocks being more likely to have high book-to-market ratios.

Another possible partial source of the size effect presented by FF (1992) and attributed to Roll (1983) and Keim (1983) is the January effect, since during their sample period the size effect is stronger in January.

As for the explanation of size as a proxy for some unknown risk factor, FF (1992) came up with four "*rational asset pricing stories*", which they deem worthy of pursuing. The first is that the size proxies some economic risk, which should be assessed by exploring the relationship between the size factor and economic variables measuring variation in business conditions. Second argues that "*the relation between size and average return proxies for a more fundamental relation between expected returns and economic risk factors*" (FF, 1992, p.450). The third route of explaining the size effect proposes that a distress factor could possibly absorb the size effect. Lastly, FF also suggest that the size effect could be caused by irrational investor behaviour, i.e., overreaction. However, they were not able to confirm any of the theories with tests.

A milestone in the size factor literature was reached by Berk et al. (1999), who came up with economic model backing the size factor. This was later expanded on by Gomes et al. (2003) and Carlson et al. (2004). Since the whole derivation of the model is too lengthy to be presented herein, only the initial step and the final equation are shown.

Berk et al.'s (1999) partial equilibrium model looks at a firm operating in an infinite horizon in discrete time, which is making investment decisions as to what projects to undertake. A project that comes along in period *j* requires an initial investment *I* and in subsequent period *t* will generate cash flow

$$C_j(t) = I * E\left(\bar{C} - \frac{1}{2}\sigma_j^2 + \sigma_j \epsilon_j(t)\right) \quad , \tag{10}$$

where $\bar{C}$ is the cash flow mean, σ_j the variance, and ϵ_j stands for the innovations. The cash flow generated by the project depends on project-specific factors as well as firm technology related factors.

The projects can be dropped or not even taken on. This is embodied in the dummy variable $\chi_j(t)$, where this variable is 0 if project is not active in period *t* and 1 otherwise. The probability of project becoming obsolete is *1-π*.

The model then goes through valuation of assets in place and growth opportunities, which together give the value of the firm.

The conditional expected return on a proportional claim on a firm is

$$E_t(1+R_{t+1}) = \frac{\pi n(t)\left[D_e[r(t)]e^{-\beta(t)}+1\right] + J_e^*[r(t)]}{n(t)D[r(t)]e^{-\beta(t)} + J^*[r(t)]} \quad , \tag{11}$$

where $D[r(t)]$ is the value of a riskless perpetual bond with depreciation rate of 1-π, $D_e[r(t)]$ is the expected value of next period perpetual bond, i.e. the expected return on the firm's assets in place, $J^*[r(t)]$ is the value of growth options, and $J_e^*[r(t)]$ is the expected value of growth options in next period. $\beta(t)$, $r(t)$, and $n(t)$ are the state variables. $\beta(t)$ is the average systemic risk of the firm's existing assets, $r(t)$ the current interest rate, and $n(t)$ the number of ongoing projects.

The number of active projects is low in the beginning of firm's lifecycle as well as in periods when there are few good investment opportunities, due to high discount rates and interest rates.

In the equation (11), "$n(t)$ *reflects the importance of existing assets relative to growth opportunities in the firm's value. It therefore determines how much of the expected return is attributable to each component of the value of the firm*" (Berk et al., 1999, p. 1566).

Therefore, in case there are no active projects, the value of the firm comes solely from the growth opportunities

$$E_t(1+R_{t+1})|_{n(t)=0} = \frac{J_e^*[r(t)]}{J^*[r(t)]} \quad . \tag{12}$$

In the opposite case, when the number of active cases is large, the growth opportunities term becomes negligible and the value of the firm is driven by the firm's assets in place. This is mathematically represented by

$$\lim_{n(t)\to\infty} E_t(1+R_{t+1}) = \frac{\pi\left[D_e[r(t)] + e^{\beta(t)}\right]}{D[r(t)]} \quad . \tag{13}$$

The variable $n(t)$ is also simultaneously measure of the firm's physical size and "*model predicts that the expected returns of smaller firms differ from those of larger firms*" (Berk et al., 1999, p. 1567). This then gives the theoretical backing to the size factor.

One question that remains unanswered is, what is the source of the underlying risk in small firms. So far, none of the avenues that researchers explored to uncover this mystery have yielded conclusive results. The most promising factors are the liquidity risk and higher information asymmetry in small firms.

However, it seems that the size effect has diminished or perhaps even disappeared over the last decades, leaving many questioning whether it is still a relevant factor and what happed to the supposed underlying risk (Crain, 2011).

Even HXZ (2012, p.3) state, that the size factor plays a second fiddle to the investment and profitability factor and was included in their model mainly to make size-related anomalies insignificant.

The prevalent theory is that smaller firms are riskier than larger firms, leading market forces to put downward pressure on their prices, resulting on higher returns on stocks of these smaller firms. However, the examination of whether this assertion still holds, in light of the size factor seemingly disappearing, would be prudent.

2.2.4 Investment factor theory

The investment factor and the profitability factor theories are based on the same two-period stochastic general equilibrium model proposed by Hou, Xue, and Zhang (2015), which was inspired by investment-based asset pricing mechanisms.

In the model there are only two periods, $t = 0{,}1$. The economy that is examined in this two-period model consists of N heterogenous firms, $i = 1, \dots, N$, and a representative household.

Each of the heterogenous firms produces a single commodity to be consumed or invested. The firm starts with productive assets (e.g., for firm i that would be A_{i0}) and produces in both periods. Each firm's productive assets (A_{it}) depreciate fully over the period when they are used. Furthermore, productive assets in period 1 equal investment for period 0, i.e. $A_{i1} = I_{i0}$. Since it is a two-period model, all firms exit at the end of period 1 with liquidation value of 0 ($P_{i1} = 0$) and there is no investment in the 2nd period. The investment I_{i0} also includes the quadratic adjustment cost $\left(\frac{a}{2}\right)\left(\frac{I_{i0}}{A_{i0}}\right)^2 A_{I0}$, i.e., cost associated with altering firm's level of output, where $a > 0$ is a constant.

The firms differ not only in their assets in place and investments, but also in their profitability. The firm's period 0 profitability π_{i0} is known at the beginning of that period. Period 1 profitability, π_{i1}, on the other hand, is subject to systemic and idiosyncratic risks. The firm's profitability is a determinant of operating cash flow, which is the product of profitability and productive assets ($\pi_{it}A_{it}$).

The representative household maximizes its utility in the two periods $U(C_0) + \rho E_0[U(C_1)]$. The utility function depends on the time preference, ρ, and consumption at time *t*, C_t. Taking the first principle of consumption results in $P_{i0} = E_0[M_1(P_{i1} + D_{i1})]$, which can be rewritten as $E_0\left[M_1 \frac{P_{i1}+D_{i1}}{P_{i0}}\right] = 1$. The P_{it} stands for the ex-dividend equity for firm *i* at a time *t* and D_{it} then stands for the dividend. When the value of the dividend is positive, it is distributed back to the households. A negative dividend on the other hand means equity injection. In period 0 the dividend equals the profit over that period, minus the investment and quadratic adjustment cost, $D_{i0} \equiv \pi_{i0}A_{i0} - I_{i0} - \left(\frac{a}{2}\right)\left(\frac{I_{i0}}{A_{i0}}\right)^2 A_{i0}$. Since all firms exit after period 1, all profit from that period is distributed, as shown by equation $D_{i1} \equiv \pi_{i1}A_{i1}$.

The last term in the first principle of consumption, M_1, is the discounting factor expressed as $M_1 \equiv \frac{\rho U'(C_1)}{U'(C_0)}$. Taking M_1 as given, household maximized the cum-dividend equity by choosing I_{i0} at the beginning of period 0, leading to

$$P_{i0} + D_{i0} = \max_{I_{i0}} \; E_0[M_1\pi_{i1}A_{i1}] + \pi_{i0}A_{i0} - I_{i0} - \frac{a}{2}\left(\frac{I_{i0}}{A_{i0}}\right)^2 A_{i0} \quad . \tag{14}$$

The first-order condition of the equation (14) is

$$\begin{gathered} E_0[M_1\pi_{i1}] - 1 - a\frac{I_{i0}}{A_{i0}} = 0 \qquad <=> \\ E_0[M_1\pi_{i1}] = 1 + a\frac{I_{i0}}{A_{i0}} \quad . \end{gathered} \tag{15}$$

The ex-dividend equity at the optimum is

$$P_{i0} = E_0[M_1\pi_{i1}A_{i1}] \quad . \tag{16}$$

Using the information that companies exit with liquidation value of 0, the definition of dividend for period 1, and equation (16), the stock return $r_{i1}^{S}=\frac{P_{i1}+D_{i1}}{P_{i0}}$, can be rewritten as

$$r_{i1}^{S}=\frac{\pi_{i1}A_{i1}}{E_0[M_1\pi_{i1}A_{i1}]}=\frac{\pi_{i1}}{E_0[M_1\pi_{i1}]} \quad . \tag{17}$$

Plugging in the result of the first order condition yields

$$r_{i1}^{S}=\frac{\pi_{i1}}{1+a\frac{I_{i0}}{A_{i0}}} \quad . \tag{18}$$

Taking the expectation of the equation (18) results in

$$E_0[r_{i1}^{S}]=\frac{E_0[\pi_{i1}]}{1+a\frac{I_{i0}}{A_{i0}}} \quad . \tag{19}$$

Equation (19) predicts that ceteris paribus high investment stocks ($\uparrow I_{i0}$) should earn lower expected returns ($\downarrow E_0[r_{i1}^{S}]$) than low investment stocks.

The intuitive explanation of the negative investment-expected return relationship is as follows: Firms invest more when they have relatively lower discounting rates, i.e. when the net present value of returns generated by the investment is high. "*Given expected cash flows, high costs of capital mean low net present values of new capital and low investment*" (HXZ, 2015, p.656) and vice versa.

HXZ (2015) also conclude that the finding that the asset growth predicts future returns with a negative slope, presented by Cooper, Gulen, and Schill (2008) is a manifestation of the investment channel. Cooper, Gulen, and Schill (2008) find that over their sample period, firms with low asset growth rates earn higher subsequent annualized risk-adjusted returns over firms with high asset growth rates.

The investment factor is also consistent with the long-term reversal effect proposed by De Bondt and Thaler (1985) and the Fama-French's HML factor. The HML factor works in the following manner, firms with high long-term prior returns, i.e., growth firms with high valuation ratios, should invest more and earn lower expected returns than firms with low long-term prior returns, i.e., value firms.

2.2.5 Profitability factor

The profitability factor is also grounded in the above-introduced two-period stochastic general equilibrium model. Equation (19) predicts that ceteris paribus high profitability stocks ($\uparrow \pi_{i1}$) should earn higher expected returns ($\uparrow E_0[r_{i1}^S]$) than low profitability stocks.

Intuitively, profitability predicts returns because "*high expected ROE relative to low investment must imply high discount rates. The high discount rates are necessary to offset the high expected ROE to induce low net present values of new capital and low investment. If the discount rates were not high enough, firms would instead observe high net present values of new capital and invest more*" (HXZ, 2015, p.652). This holds vice versa for low expected ROE.

The profitability channel is consistent, e.g., with the standard discounting model and with momentum effect. Firms with positive profitability stocks tend to outperform stocks with negative profitability in the short run.

2.3 Manufacturing sector

The U.S. is the largest manufacturer in the world, with approximately 18% of the world's goods being produced there in 2008. However, the growth of the U.S. manufacturing sector is trailing behind the overall U.S. economy, as well as behind the growth of the manufacturing sector in many other countries (Thomas, 2012). This is by no means a short-term trend. In the 50 years following 1957 the average annual 10-year growth has dropped from 5% to -1% (Thomas, 2012).

Even so, manufacturing is still largely important for the U.S. economy and warrants a deeper analysis as to what risk factors play the key roles and if that differs from the market as a whole. That is why the manufacturing sector has been chosen as the topic of this thesis. Furthermore, manufacturing is the only sector with enough stocks to get an adequate sample for the construction of the q-factors.

The manufacturing sector has been examined only briefly by Hou, Xue, and Zhang (2012) in Table 9. The table reports the results of regression of excess returns of ten industry portfolios on the CAPM model, Fama-French three-factor model, Carhart four-factor model and the q-factor model. The manufacturing sector is one of these industry portfolios. For the manufacturing sector, the q-factor has the highest alpha among the competitors, in absolute terms, and even though its t-score is not significant, at 1.57 it is over twice as high as the alpha t-score of any other competing model. All the q-factors apart from the size factor have statistically significant coefficients, although for the investment and profitability factors these coefficients are significantly lower than the coefficient of the excess market return.

This suggests that the q-factor model is not the best fit for explanation of return on the manufacturing sector and there could be differences between the q-factors constructed from the manufacturing stocks and the non-manufacturing stocks.

2.3.1 Market factor in manufacturing sector

There is generally a lack of theoretical literature exploring the link between returns on the whole economy versus return on its sectors. That is probably due to the fact, that empirically there seems to be no link to explore, at least for the manufacturing sector.

Comparison of returns on ETFs created from the whole economy as opposed to industrials shows that there is little difference between the two. More precisely, the Vanguard Total Stock Market ETF performs slightly worse than the Vanguard Industrials ETF in the September 2004 to December 2019 period. The Vanguard Total Stock Market ETF returned on average 0.69% per month, the Vanguard Industrials ETF returned 0.76% per month, and the correlation of the returns is 0.94. The paired two-sample means t-statistic is only -0.45, so the hypothesis that the average returns on the two ETFs are equal cannot be rejected. This is also visible in Figure 2, where the indices of the ETFs co-move almost perfectly.

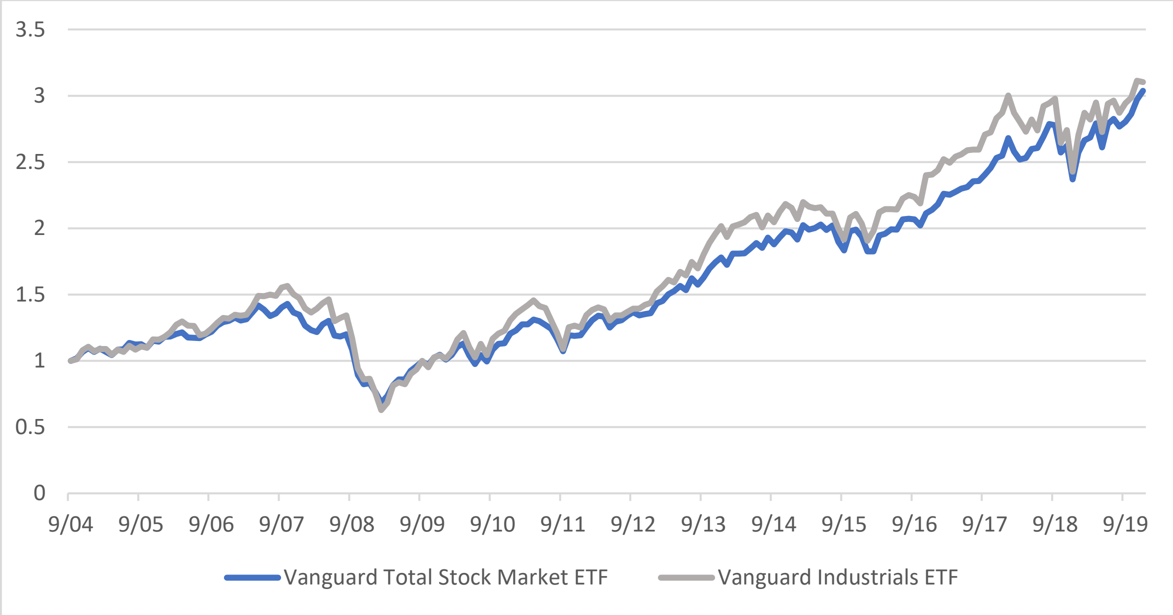

Figure 2 - Vanguard indices (base September 2004)

The story is similar for the S&P 500 indices. However, here the whole market performs almost exactly as well as the industrials, one thousandth of a percent better in fact. The correlation in this case is 0.93 and the t-statistics for the paired two-sample means t-test is 0.006. The relationship between the S&P 500 total return index and the S&P 500 industrials total return index is graphically shown in Figure 3.

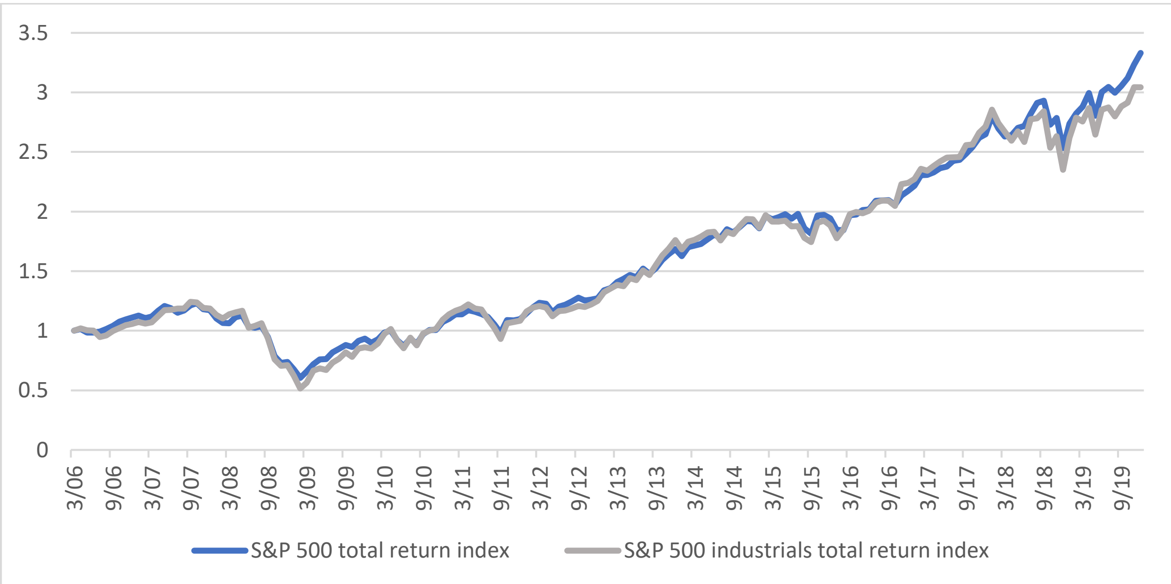

Figure 3 - S&P 500 indices (base March 2006)

Based on these empirical observations, and the lack of theory stating otherwise, the excess market return factor hypothesis is that there will be no difference between the market factor constructed for the non-manufacturing stocks and the one constructed from the manufacturing stocks.

2.3.2 Size factor in manufacturing sector

Similarly to the market factor, there is not much theory available that would predict and explain the difference between the size factor constructed from the whole economy as opposed to manufacturing sector. However, the share of small business employment in the manufacturing sector was a bit lower than the economy average for the year 2015. The small business employment share in the manufacturing industry was 44.4%, whereas for the overall it was 47.5% (The Office of Advocacy of the U.S. Small Business Administration, 2018). If these proportions from the year 2015 hold similarly for the whole sample period investigated herein, then that means that on average smaller portion of the manufacturing companies are small in contrast to the whole economy. If that is the case the expectation is that on average the manufacturing size factor should be a little bit lower than the size factor constructed from the stocks of the whole economy.

However, the difference between the shares of small business employment of the whole economy and manufacturing sector is slight and as previously stated there is a lack of theoretical literature specifically exploring the relationship between the size factor and the manufacturing sector. It is, therefore, highly likely that the difference will not be statistically significant, or the results will be significant only due to the timeframe choice.

The size factor hypothesis is therefore that if there any difference at all, the returns of the size factor constructed from the non-manufacturing stocks should be higher than returns from the size factor constructed solely from manufacturing stocks.

2.3.3 Investment factor in manufacturing sector

Fernando and Mulier (2015) study links between financial constraints for external financing and other variables, one of which is leverage. They hypothesised and empirically showed positive relation between leverage and financial constraints. That means they showed that the lower the leverage ratios, the less likely is the firm to experience financial constraints. Firms with high leverage on the other hand are likely to find it costly and difficult to take on additional debt. Although this paper uses data from the ECB and European Commission survey and AMADEUS database, the theoretical explanation of the leverage and financial constraints is likely to hold even in case of US companies.

The negative investment-expected return relation is then intuitively explained in the Hou, Xue, and Zhang (2015) paper, "*Firms invest more when their marginal q (the net present value of future cash flows generated from an additional unit of assets) is high. Given expected profitability or cash flows, low discount rates imply high marginal q and high investment, and high discount rates imply low marginal q and low investment. […] Given expected cash flows, high costs of capital imply low net present values of new projects and low investment, and low costs of capital imply high net present values of new projects and high investment*" (HXZ, 2015, pg. 655).

This means that firms with high leverage, which can be thought to have high financial constraints and high cost of capital, should ceteris paribus have low investment. This holds vice versa for firms with low leverage, which have high investment.

The leverage levels are significantly different among the manufacturing industries. In table 4 of the Bernanke et al. (1990) paper, the range of the debt to asset ratio of manufacturing industries is wider than that of other industries in all timeframes. This means that there is more significant difference of level of leverage within the manufacturing sector than there is in the rest of the economy.

Based on the abovementioned arguments, the investment factor hypothesis is that the investment factor created from the manufacturing sector stocks only will be higher than the investment factor created from the rest of the economy.

2.3.4 Profitability factor in manufacturing sector

Baker (1973) introduced a model showing that the leverage and profitability are positively correlated, i.e., higher leverage implies higher industry profitability and vice versa. Furthermore, the paper suggested that industries have common determinants of leverage levels, that is that the selection of leverage within an industry is determined by industry conditions such as cost fixity and output predictability.

Fernando and Mulier (2015) likewise explored the relation of leverage and profitability and also came to a conclusion that there is a positive correlation between the two. They assert that "*firms with higher debt-to-asset ratios need higher profits to be able to repay their debt*" (Fernando and Mulier, 2015, pg. 19).

The manufacturing sector in the US has historically had significantly lower leverage than the overall economy. In the sample in Bernanke et al. (1990) the average debt to assets ratio of the manufacturing sector was about 80% of the whole sample.

Since the manufacturing sector has overall lower leverage than the whole economy and the leverage is positively correlated with profitability, the profitability factor hypothesis is as follows: The profitability factor created from the manufacturing sector stocks only will be lower than the profitability factor created from the whole sample.

The relationship between manufacturing and profitability was also examined empirically by Lifschutz (2019), who indicated that industries in the manufacturing sector do not belong to the most profitable ones. Lifschutz (2019) concluded, that manufacturing sector "*generate[d] relatively low profit margins, with the sector's average margin total[l]ing 8.2% of annual revenue in 2019.*" This also suggests that the range of profit margins of manufacturing stocks will be smaller than the range of profit margins of non-manufacturing stocks.

The same conclusion can be drawn directly from the data available on the website of the IFRS financial reporting and analysis software Ready Ratios ([45]), which shows the gross margin medians by industry for the years 2015-2019. The difference in the profit margins between the most and least profitable manufacturing industries, manufacturing industries being those with index between 20 and 39, is about half that of the whole economy. Furthermore, in none of the years do the most or least profitable industry belong to the manufacturing sector.

Since it seems, that the manufacturing stocks are not at either extreme, this supports the hypothesis, that the profitability factor constructed on the manufacturing stocks will be on average lower, when compared to the rest of the economy.

2.3.5 Hypotheses

In summation, there are four hypotheses, each corresponding to one of the factors in the q-factor model, i.e., excess market return factor, size factor, investment factor, and profitability factor. These hypotheses are restated below.

Excess market return factor hypothesis: The excess market return factor created from the manufacturing sector stocks only will not be significantly different from the excess market return factor constructed from the rest of the economy.

Size factor hypothesis: The size factor created from the manufacturing sector stocks only will be lower than the size factor constructed from the rest of the economy.

Investment factor hypothesis: The investment factor created from the manufacturing sector stocks only will be higher than the investment factor constructed from the rest of the economy.

Profitability factor hypothesis: The profitability factor created from the manufacturing sector stocks only will be lower than the profitability factor constructed from the rest of the economy.

3 Research material and methods

3.1 Data

The data used is downloaded from the Wharton Research Data Services (WRDS) database, namely Center for research in Security prices (CRSP) and Compustat databases. The final dataframe spans from January 1967 to December 2019. Therefore, due to the different periods it takes to construct the variables, the date ranges for the individual databases vary.

Other than the CRSP monthly stock database, the CCMA database and the CCMQ database, additional databases are used. The risk-free rate is approximated by the 3-month treasury bill, data for which was taken from Reuters and additional databases are used in dealing with delisting returns. Specifics of the delisting returns databases and methodology used are discussed in appendix B.

3.1.1 CRSP Monthly stock database

The CRSP Monthly stock database is used for the prices and returns information. Namely, the downloaded variables are the holding period return (RET), delisting return (DLRET), delisting code (DLSTCD), price (PRC), shares outstanding (SHROUT), and the SIC code (SICCD).

The date range used is from December 1966 to December 2019. This is because of the need for one additional period (month) before January 1967 (the beginning of our final dataframe), for the construction of lag of size variable (size = SHROUT * PRC).

HXZ (2015, p. 5) also impose constraint on what exchanges are to be included in the sample. The selected exchanges are NYSE, AMEX, and NASDAQ. The filtering is done on the CRSP database, because filtering the CCM databases on this criterion would lead to a significant lag between a company being listed on the selected stock exchange and it entering the factor creation. This is also supported by the empirical finding, that filtering exchanges on both CRSP and CCM databases leads to number of total observations in the final dataset being lower and the magnitudes of return on the factors being different from what HXZ report on their data website ([33]).

One additional constraint chosen, also imposed by Fama French (2015, p. 3) and George et al. (2018, p. 10), is selecting only ordinary shares (SHRCD 10 or 11) and filtering out all the other securities included in the database.

3.1.2 CCMA database

The annual accounting variables are taken from quarterly updated CRSP/Compustat Merged - Fundamentals Annual (CCMA) database. CCMA is a Compustat Fundamentals Annual database with the corresponding security and company identifier (LPERMNO and LPERMCO), which embody the link to the CRSP database.

The database is used for the I/A variable construction as well as extension of the ROE variable. The variables downloaded from this database are total assets (AT), total liabilities (LT), stockholders' equity (SEQ), total common equity (CEQ), deferred taxes (TXDITC) preferred stocks – total (PSTK), redemption value (PSTKRV), and liquidation value (PSTKL), common shares outstanding (CSHO), share adjustment factor (AJEX), and SIC code (SIC).

The time range is from July 1964 to June 2019. That is due to the fact that to construct the January to June 1967 I/A variable the 1965 and 1964 total asset variable can be needed as AT and lag of AT. Further restrictions placed on the data are outlined in Appendix A.

3.1.3 CCMQ database

The quarterly accounting variables are taken from quarterly updated CRSP/Compustat Merged - Fundamentals Quarterly (CCMQ) database. CCMQ is a Compustat Fundamentals Quarterly database with the corresponding security and company identifier (LPERMNO and LPERMCO), which embody the link to the CRSP database.

The variables downloaded from the CCMQ database are used for construction of the ROE factor. Many of the variables are quarterly versions of the ones downloaded from the CCMA database with a Q appended to the end of the variable name. These variables are ATQ, LTQ, SEQQ, CEQQ, TXDITCQ, PSTKQ, CSHOQ, and AJEXQ. Apart from these there are additional variables downloaded and those are the income before extraordinary items (IBQ), redeemable preferred stocks (PSTKRQ), ex-date dividends per share (DVPSXQ), and the report date of quarterly earnings (RDQ).

The time range is from December 1964 to December 2019. This is due to the possible lag in assignment of ROE variable values and the ROE forward imputation extension. The constraints placed on the data downloaded from this database are identical to those imposed on CCMA, i.e., those mentioned in appendix A.

3.2 Methodology

3.2.1 Data clean-up

A. CRSP

As the first step in cleaning up the CRSP dataframe, prices (PRC) must be set to their absolute value, in order to get rid of the negative prices. Negative prices are CRSP's convention indicating that actual closing price for the trading day was not available, so the average of bid and ask price was taken ([10]).

Another issue is the key of this database, which is PERMNO (security-level identifier) and date. This is the database key, because a single company can have multiple securities (i.e. for some of the PERMCOs there are multiple corresponding PERMNOs). However, the size factor could be distorted if a PERMNO with the largest market capitalization is simply taken for each company. This would be a problem for example if two PERMNOs from one company (with identical PERMCO) during the same period (with identical date) were to be labelled as small, even though the company would make the cut-off to be classified as large.

In order to get rid of the duplicates in the PERMCO - date key, the following method is used:

1. Create variable size by multiplying number of shares outstanding and the stock's price (SHROUT * PRC).
2. Get the one month lag of price (PRC) and size, these shall be referred to as lagprice and lagsize.
3. Find the PERMNO with the largest lagsize and exclude all the other PERMNOs with the same PERMCO and date from the cleaned-up dataframe.

4. Set the size for the given PERMCO and date as the sum of sizes of the corresponding PERMNOs. Analogically the lagsize variable is also re-set to reflects the size of the company more faithfully.

After making the PERMCO and date the key of this dataframe another step is to deal with the fact that for a couple of observations there is ‘C’ wrongly assigned to RET. ‘C’ is supposed to denote instances where the lagprice is not available for the observation, however, that is not always the case. For these wrongly assigned returns the return is computed following the CRSP manual to return computation ([10], pp. 101) as $RET_t = \frac{PRC_t}{lagprice} - 1 = \frac{PRC_t}{PRC_{t-1}} - 1$, if dividend cash amount (DIVAMT) is nan and $RET_t = \frac{PRC_t * FACPR + DIVAMT}{lagprice} - 1 = \frac{PRC_t * FACPR + DIVAMT}{PRC_{t-1}} - 1$, otherwise. The FACPR in this equation is the factor to adjust price.

The next step is to account for delisting returns, in order to avoid bias. For this step, the approach is taken from Beaver et al. (2007, pp. 7-9) with the adjustment made by HXZ (2017b, pp. 127 - 128). The inclusion of delisting returns involves compounding returns in the period when the delisting takes place with the delisting return. The details of the method used are described in appendix B.

After this, the financial firms, i.e. the companies with SIC code (SICCD) starting with the number 6, are deleted from the dataframe ([49]). This is done in accordance with the restrictions employed by HXZ (2015, pp.659).

As the last step of the CRSP data clean-up the penny stocks are excluded. Urbański et al. (2014) show on case of Warsaw stocks that including penny stocks contributes to inconsistent pricing. An easy way to exclude penny stocks is to filter stocks on a minimum required price. Since HXZ do not specify at what price the stocks should be filtered, the chosen cut-off for the analysis is 1 US dollar.

B. CCMA

In the CCMA dataframe there are a few duplicates in the PERMNO - year key. This arises from a few securities having two annual reporting dates (presumably from change in their fiscal year choice). Since the most recent information depicts the state of the company most faithfully, that is the one that is kept. The previous observation for that year is removed from the dataframe.

Subsequently the duplicates in the PERMCO-year are removed. This is done by keeping just any of the duplicates. Since for all securities of one company the company data remains the same and PERMCO is used to link the dataframes, it is immaterial which particular PERMNO is kept.

Finally, the financial firms are deleted from the dataframe. This once again mean deleting observations with the SIC code beginning with 6, i.e., from 6000 to 6999 ([49]). In the case of the CCM databases the SIC codes are contained in variable SIC.

C. CCMQ

Similarly to CCMA, in the CCMQ dataframe there are also some duplicates in the PERMNO – datadate key. This seems to once again be caused by firms changing its fiscal year end. That is why the observation differ in what fiscal quarter they are attributed to ([11], DATACQTR). To deal with the duplicates, the observation with fewer non-missing variables is kept. If both observations have the same number of non-missing variables, the latter one is kept. There is no theoretical backing for this approach, but the duplicates account for only 0.1% of the data, so any variation in approaches in this case is unlikely to influence the outcome in any meaningful manner.

The penultimate and final step in the CCMQ clean-up are analogous to the ones implemented in CCMA. Namely, deleting PERMCO-datadate duplicates and deleting financial firms from the data set.

3.2.2 Variables creation

A. ME variable

The size variable is created by multiplying the CRSP's shares outstanding (SHROUT) with CRSP's stock price (PRC). The equation is as follows, $ME_t = SHROUT_t * PRC_t$. The lower letter *t* stands for the month *t*.

B. I/A variable

The investment variable is the year t total assets (AT) from the CCMA database minus one year lagged total assets divided by the lagged total assets. Expressed in equation terms the investment variable is $I/A_t = \frac{AT_t - AT_{t-1}}{AT_{t-1}}$. The t in this case stands for the year t.

C. ROE variable

The profitability variable is created by taking CCMQ's income before extraordinary items (IBQ) and dividing it by one quarter lagged book equity, i.e. $ROE_t = \frac{IBQ_t}{Book\ equity_{t-1}}$. There are four approaches to finding the book equity. The original approach to computing book equity was introduced in Hou, Xue, and Zhang (2012). The three extensions introduced by Hou, Mo, Xue, and Zhang (2019) help expand the sample from 1972 to 1967. The first extension is for the fourth quarter book equities using CCMA annual data. The second extension is based on backward imputation and the third on forward imputation.

Whenever possible the basic approach to calculate book equity is employed. In this approach the data is taken from the CCMQ database. The book equity is calculated as book value of preferred stock subtracted from shareholder equity plus deferred taxes & investment tax credit (TXDITCQ), if available. That is $Book\ equity = Shareholder\ equity - Book\ value\ of\ preferred\ stock\ + TXDITCQ\ (if\ available)$.

The shareholder equity is computed based on available data in one of three following ways. The primary way is to take the stockholder's equity (SEQQ), the secondary way is to add common equity (CEQQ) and preferred stock (PSTKQ), and the third is to subtract total liabilities (LTQ) from total assets (ATQ).

The book value of preferred stock is either redeemable preferred stock variable (PSTKRQ) from CCMQ database, or in case that is not available, the total preferred stock (PSTKQ) also from the CCMQ database.

The first extension, i.e. the extension for the fourth quarter period, is based on exactly the same formulas as the original approach. The only difference is that the data is taken from the CCMA annual fundamentals database and therefore the variables do not have the letter "Q" at the end.

If neither of the previous approaches work, the backward imputation is used whenever the book equity variable is available for the quarter following the one being computed. Since the lag of book equity is used in the construction of ROE variable, this does not pose a lookahead bias. In the backward imputation approach the next quarter's income before extraordinary items (IBQ from CCMQ) is subtracted from next quarter book equity and next quarter dividends are added to get this quarter's book equity. The equation is $BKEQ_t = BKEQ_{t+1} - IBQ_{t+1} + Quarter\ dividend_{t+1}$.

The quarter dividend is 0 if the ex-date quarter dividend per share (DVPSXQ from CCMQ) is 0. Otherwise the quarter dividend is $DVQ_{t+1} = DVPSXQ_{t+1} * shares\ outstanding_t * \frac{\text{cumulative share adjustment factor}_t}{\text{cumulative share adjustment factor}_{t+1}}$.

Depending on availability the shares outstanding are either the variable CSHOQ from the CCMQ database, or CSHO from the CCMA database for the fourth quarter. If neither is available the SHROUT variable from the CRSP database is used instead.

The cumulative share adjustment factor is also dependant on the availability of the data, primarily the CCMQ database is used, namely the AJEXQ variable, secondarily the CCMA database, more precisely the AJEX variable, is chosen in case of fourth quarter data, and lastly the CRSP's CFACSHR.

When none of the previous approaches work, the forward imputation is used, provided that the book equity variable is available at most 4 periods prior to the computed one. This method is analogous to the backward imputation and can be expressed as $BKEQ_t = BKEQ_{t-j} + \sum_{i=0}^{j-1}(IBQ_{t-i} - Quarter\ dividend_{t-i})$, where $1 \leq j \leq 4$. The computation and order of construction variables in the quarter dividend is the same as in the backward imputation approach.

3.2.3 Assignment into groups

A. ME groups

At the end of June, the size breakpoint – the median of NYSE stock size - is computed and based on this breakpoint all stocks from the end of June are assigned to groups. Group 1 contains the smaller stocks, with size below the median and group 2 contains the larger stocks. These assignments are then used from July onward till June of next year.

B. I/A groups

At the end of June, the I/A variables from the previous year are taken and two breakpoints are computed. The breakpoints are once again computed only from the NYSE stocks. The lower breakpoint is the 30^{th} percentile and the upper one is the 70^{th} percentile. Based on these two breakpoints the stocks are assigned to three I/A groups, group 1, 2, and 3, with the group 1 being lower than the 30^{th} percentile, group 3 being higher or equal to the 70^{th} percentile and group 2 in between.

C. ROE groups

The ROE values which are in quarterly form are used in the months following the quarterly earnings announcement dates (RDQ). If RDQ is missing the ROE values are used from the 4^{th} month after the end of quarter date onwards. To exclude stale earnings another restriction imposed is that stocks enter group assignment only if the end of quarter date is within 6 months of portfolio construction.

Each month the ROE values are taken and split into 3 groups based on NYSE 30th and 70th percentile breakpoints. Group 1 contains the stocks with lowest ROE and group 3 with those with highest ROE.

3.2.4 Factors creation

The intersection of ME, I/A, and ROE groups forms 18 portfolios. For each portfolio the value-weighted returns are calculated. The portfolios are rebalanced monthly. The returns on the portfolios are then the construction pieces of the size factor, the investment factor, and the profitability factor.

A. Excess market return factor r_{MKT}

The excess market return factor (r_{MKT}) is the value weighted return on all stocks minus the risk free rate.

B. Size factor r_{ME}

The size factor (r_{ME}) is calculated similarly to Fama-French's SMB factor, i.e., by taking a simple average of the 9 small size portfolios value weighted returns and subtracting the simple average of value weighted returns on the 9 large portfolios.

C. Investment factor $r_{I/A}$

The investment factor ($r_{I/A}$) is calculated by taking the difference between low investment and high investment portfolios. More precisely by taking the average of returns on the 6 low I/A portfolios and subtracting from it the average of returns on the 6 high I/A portfolios.

D. Profitability factor r_{ROE}

The ROE factor (r_{ROE}) is computed by subtracting the returns on the six low ROE portfolios from the returns on the six high ROE portfolios. Thus, each month we get high-minus-low ROE portfolios returns, and that is the portfolio factor.

3.2.5 Manufacturing

In order to price the US manufacturing sector stocks with the q-factor model the methodology outlined in parts 3.2.2 to 3.2.4 is employed on manufacturing stocks. For a stock to be classified as manufacturing stock it has to have SIC code between 2000 and 3999 ([49]). In turn the non-manufacturing stocks are stocks with the SIC code either below 2000 or over 3999.

4 Results

4.1 Empirical properties of the factors constructed from all US stocks

As can be seen in Table 1, the q-factor model results on the whole dataset are highly similar to those presented by HXZ in their dataset ([33]). All factors have over 97% correlation with their counterparts and they differ at most by 0.05% in all periods. The high correlation is also apparent in the graphs presented in Figure 4.

The market excess return factor has the highest correlation with its counterpart, 99.86%. This is even higher for the FF market factor, 99.99%. That is why in Table 3 the FF market factor is omitted from the correlations table. However, the paired sample t-test shows that there is a significant difference between the means of the market excess return factor calculated from the HXZ data and the one constructed based on the methodology outlined herein. The computed mean abnormal return is 0.56% per month, similar to the 0.55% computed by FF. On the other hand, the excess market return mean calculated from the HXZ data is only 0.53%.

After the market factor, the size factor has the fewest apparent outliers from the trend line (Figure 4). That is in line with the fact that it has the second highest correlation. However, the slope of the trend line and the difference in means indicate that on average the returns computed for the size factor, following the methodology outlined in part 3, are lower than those from HXZ data. Nevertheless, the paired sample t-test suggests that the null hypothesis that the mean difference between paired observations is zero, is not rejected.

That is not the same case for the investment factor, whose paired sample t-test suggests that the HXZ factors' returns and the computed factor returns are different with statistical significance. This is consistent with the relatively large difference between the means. Furthermore, the correlation is lower than that of the other factors. However, correlation of 97% suggests that the investment factor returns are still highly similar.

Contrary to the size and investment factor, the profitability factor created following the methodology outlined in part 3 is imperceptibly higher than the one computed from the HXZ data. Furthermore, the t-statistics of the computed mean is also higher than the HXZ one. However, the paired sample t-test suggests that the difference profitability factors returns' means is negligible. The overall correlation of the profitability factor computed from the HXZ data with the one computed with the methodology outlined herein is 98%.

Table 1 - Properties of the q-factors and comparison to HXZ

	Mean *(t-stats)*	*HXZ mean* *(t-stats)*	*Correlation* *(p-values)*	*Paired sample t-test*
r_{MKT}	0.56	0.53	1.00	-2.72
	(3.15)	(3.00)	(0.00)	
r_{ME}	0.26	0.27	0.99	1.08
	(2.18)	(2.27)	(0.00)	
$r_{I/A}$	0.32	0.36	0.97	2.72
	(4.27)	(4.87)	(0.00)	
r_{ROE}	0.54	0.54	0.98	-0.12
	(5.58)	(5.45)	(0.00)	

The mean in the first column is the average monthly return (in percentage terms) on the q-factors calculated in accordance with methodology outlined in part 3 hereof. The HXZ mean is the average monthly return (in percentage terms) on q-factor calculated by Hou, Xue, and Zhang. The correlation and the paired sample t-test are calculated from corresponding factors from these 2 different sources, i.e., from returns on factors calculated herein and from returns on factors provided by Hou, Xue, and Zhang. The excess market return factor is denoted as r_{MKT}, the size factor as r_{ME}, the investment factor as $r_{I/A}$, and the profitability factor as r_{ROE}.

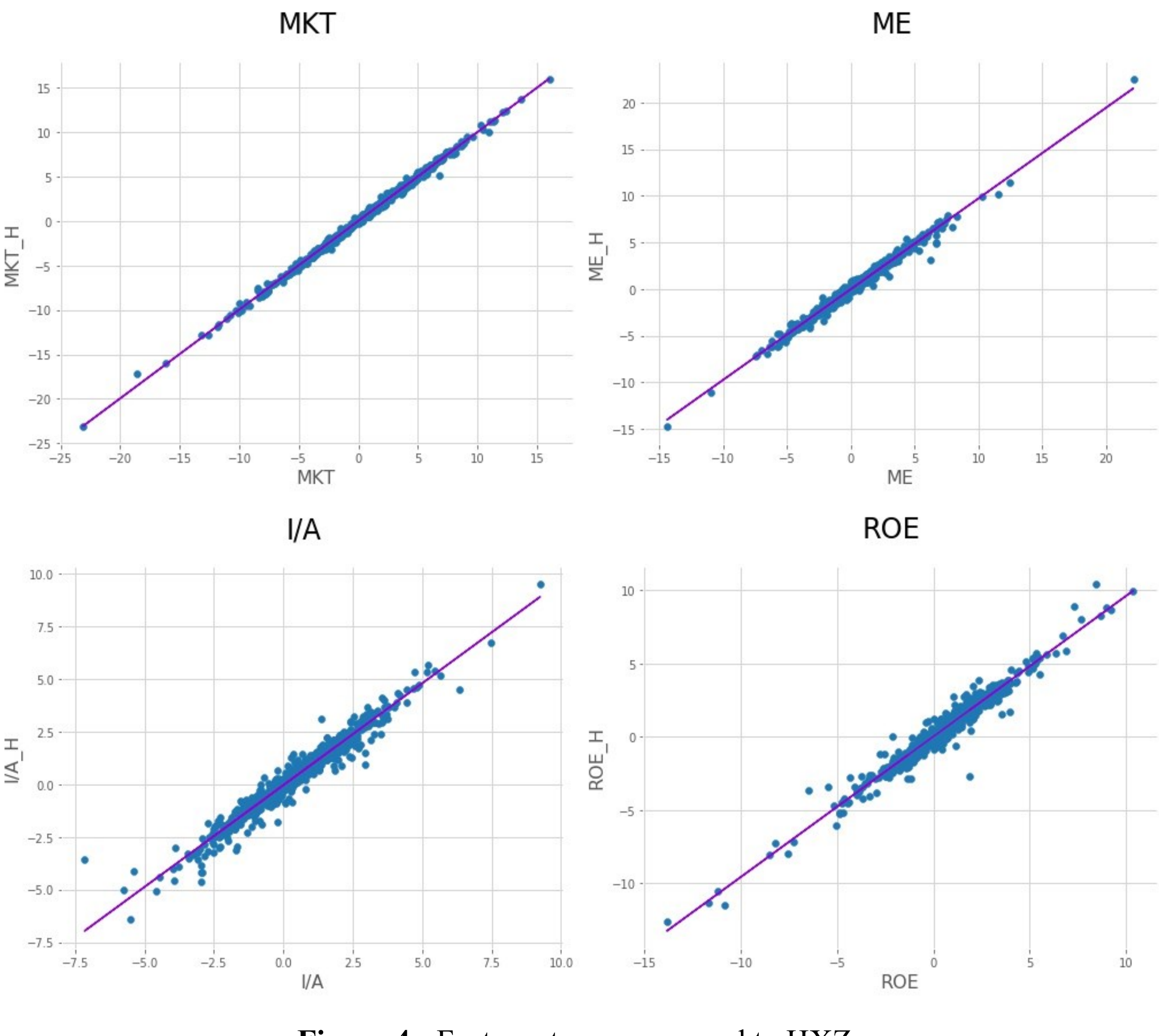

Figure 4 - Factor returns compared to HXZ

The correlation of the total sample size, i.e. the number of companies included in the underlying portfolios in the q-factors construction, is also high, 97%. Visually this is shown in Figure 5. As for the 18 underlying portfolios formed by intersection of the ME, I/A, and ROE group assignments, the results of their returns and their number of constituents are presented in Table 2. The return correlations are over 98% and sample size correlations are on average 95% with the lowest one being 84%. Furthermore, for most of the groups the paired sample t-test values of their returns are not significant at any reasonable level. The only significant difference in the groups is in the sample sizes, which are significantly different between the calculated groups and HXZ groups.

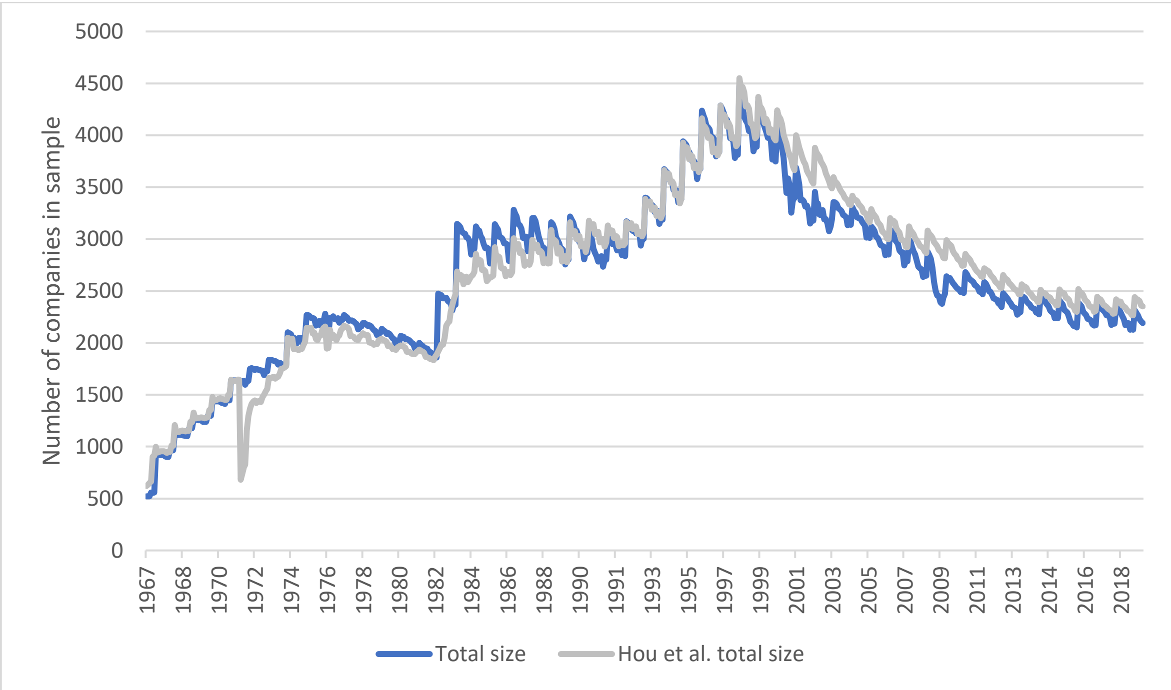

Figure 5 - Correlation of total sample sizes

Table 2 - Returns and number of constituents of underlying portfolios

Portfolio		*111*	*112*	*113*	*121*	*122*	*123*	*131*	*132*	*133*
Return	mean	0.93	1.41	1.67	1.02	1.29	1.61	0.34	0.96	1.38
	mean_H	0.99	1.44	1.72	1.02	1.29	1.66	0.37	0.94	1.38
	correlation	1.00	0.99	0.99	0.99	0.99	0.99	0.99	0.99	0.99
	(pair t-test)	2.18	0.85	1.31	-0.14	0.30	1.63	0.92	-0.85	-0.07
# of const.	correlation	0.94	0.96	0.96	0.98	0.99	0.97	0.98	0.99	0.99
	(pair t-test)	-11.2	-0.5	6.7	0.7	3.2	13.9	-0.3	4.2	17.9
Portfolio		*211*	*212*	*213*	*221*	*222*	*223*	*231*	*232*	*233*
Return	mean	0.91	0.97	1.20	0.81	0.94	1.00	0.63	0.82	1.07
	mean_H	0.98	1.01	1.15	0.83	0.94	1.00	0.52	0.84	1.06
	correlation	0.98	0.99	0.99	0.99	0.99	1.00	0.98	0.99	1.00
	(pair t-test)	1.50	1.61	-2.05	0.66	0.14	-0.47	-2.32	0.63	-0.98
# of const.	correlation	0.93	0.89	0.98	0.90	0.84	0.93	0.99	0.94	0.94
	(pair t-test)	-4.0	-14.9	-6.9	-3.1	-12.0	-7.8	-12.3	-15.8	-6.7

For each underlying portfolio the mean of the monthly returns on this portfolio is calculated with the methodology presented in part 3 hereof and the Hou, Xue, and Zhang data. Additionally, correlation and paired sample t-test of the returns on the underlying portfolios and the number of constituents of the underlying portfolios are presented. The underlying portfolios are named based on the groups their constituents belong to. The first number shows which size group the stocks belong to, the second number is for investment and the third for profitability group.

The correlation of the q-factors with Fama French factors is shown in Table 3. The q-factor model size factor is negatively and significantly correlated with the investment and profitability factors. Unsurprisingly, it has also around 97% correlation with the Fama French size factor.

The investment factor has a high, 91%, correlation with the Fama French CMA factor. CMA (Conservative Minus Aggressive) factor is defined as the "*difference between the returns on diversified portfolios of the stocks of low and high investment firms, which [Fama and French] call conservative and aggressive*" (Fama-French, 2015, pg. 3). It also has a 67% correlation with the HML factor (value minus growth portfolios), which is not surprising, given the high correlation between CMA and HML factor ([19]).

The profitability factor is the most unique out of all of the factors, in that it has the lowest correlation with the other variables. The highest correlation is 67% with RMW (Robust Minus Weak) factor, which is based on operating profitability portfolios.

Table 3 - Correlations and (p-values) of the Q-factor model and Fama French factors

	ME	*I/A*	*ROE*	*Mkt-RF*	*SMB*	*HML*	*RMW*	*CMA*
ME	1							
	(0.00)							
I/A	-0.12	1						
	(0.00)	(0.00)						
ROE	-0.31	0.04	1					
	(0.00)	(0.34)	(0.00)					
Mkt-RF	0.26	-0.39	-0.20	1				
	(0.00)	(0.00)	(0.00)	(0.00)				
SMB	0.97	-0.17	-0.39	0.28	1			
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)			
HML	-0.02	0.67	-0.13	-0.26	-0.07	1		
	(0.60)	(0.00)	(0.00)	(0.00)	(0.10)	(0.00)		
RMW	-0.36	0.07	0.67	-0.23	-0.36	0.08	1	
	(0.00)	(0.08)	(0.00)	(0.00)	(0.00)	(0.04)	(0.00)	
CMA	-0.04	0.91	-0.07	-0.40	-0.09	0.70	-0.01	1
	(0.29)	(0.00)	(0.10)	(0.00)	(0.02)	(0.00)	(0.75)	(0.00)

The correlations and their p-values are presented for the returns on the q-factors and the FF5 model factors. Due to high correlation of the market factor calculated based on the methodology presented in part 3 hereof and the market factor from FF data, the factor is included just once.

Overall, the results obtained by following the methodology outlined in section 3 are very similar to those presented by HXZ on their data website ([33]). Hou, Xue, and Zhang do not detail all steps of filtering and restrictions they impose on their data, which accounts for the above presented small deviations. Nevertheless, these deviations are negligible enough as to infer a high degree of similarity of the methodologies employed.

4.2 Empirical properties of the factors constructed from US manufacturing stocks

HXZ (2017a, p. 7) state that they require each of the 18 portfolios from the triple sort on size, I/A, and ROE to contain at least ten firms. However, from the benchmark portfolios provided by HXZ ([33]) it is clear that this is not such a strict rule as it might appear. Therefore, the rule employed herein is that each benchmark portfolio has to have at least eight constituents, to balance the number of the periods in sample against the possibility of outliers.

Having the afore-outlined minimum number of observations requirement leads to shortening the sample period, which starts from January 1992 and spans till December 2019.

Both the results for this shortened sample period and the total one starting 1967 are reported below. As the short period might not be long enough to provide statistically significant results or to assess the factor in the full context, the longer sample period is reported as well. This serves as a robustness check in the analysis.

As shown in Figure 6 manufacturing sector accounts in total for 53% of the observations in the US market in the 1967-2019 period. The proportion of the manufacturing stocks in the sample has fallen over the sample period and in 2019 manufacturing stocks accounted only for about 38% of all stocks in the sample. Overall, the size of the sample rose to its high in around 2000 and then fell to its pre-1982 levels in 2019.

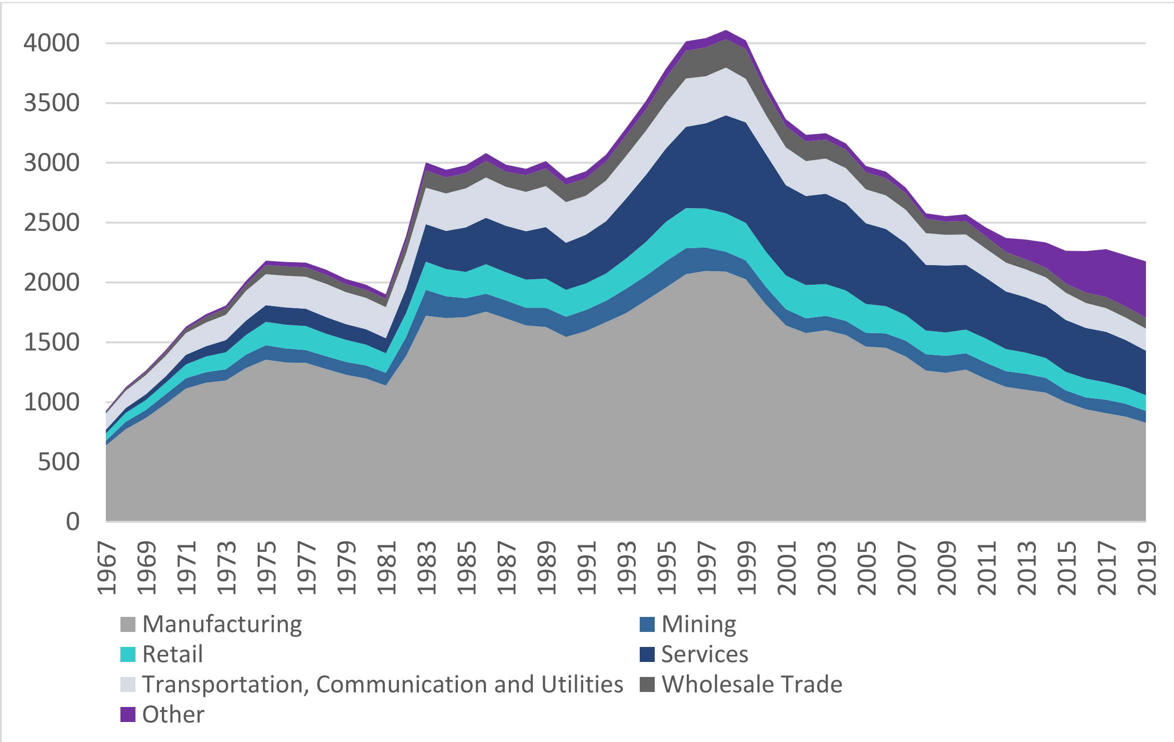

Figure 6 - Breakdown of the average annual observations by sector

Figure 7 visualizes how the sample shrinks when only stocks with data available for I/A, ME, and ROE variable are selected. The size of the final sample seems to, largely, comove with the number of stocks in the CRSP database. As for the share of manufacturing stocks, there is a discernible discrepancy between the share of manufacturing stocks in the CRSP database and the share of manufacturing stocks in the final sample. This suggests that companies in the manufacturing sector are on average better at reporting their accounting data than companies from the rest of the economy.

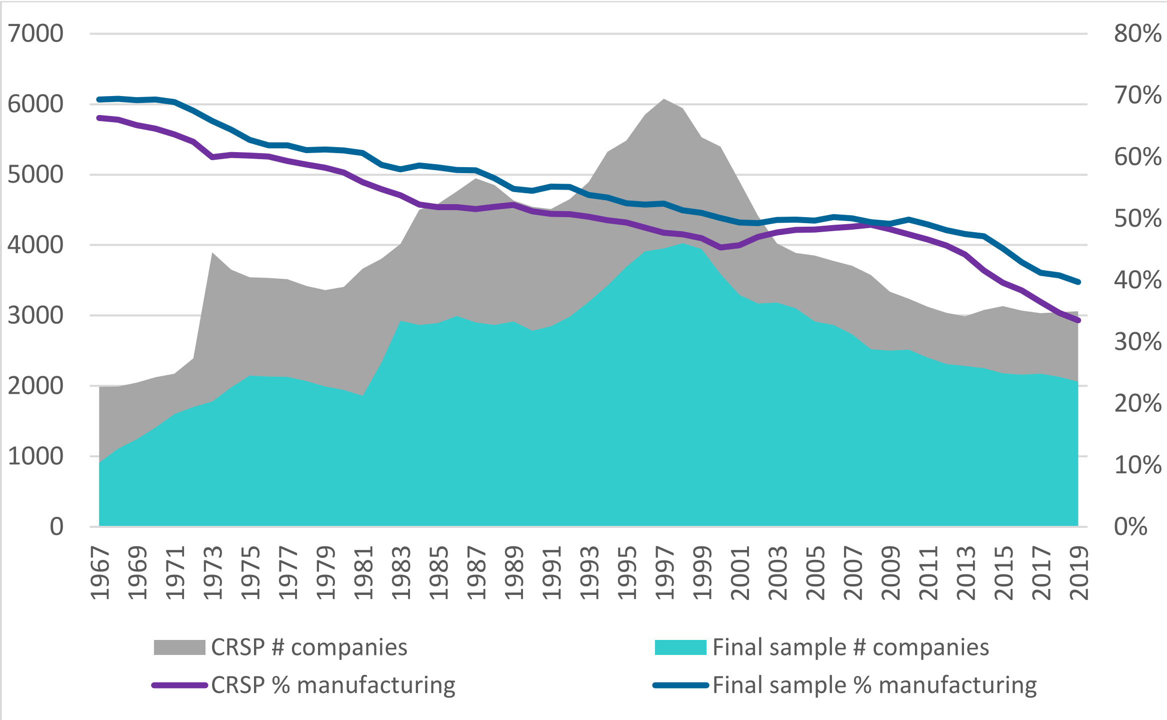

Figure 7 - Annual average number of companies with SIC code in CRSP and final sample and share of manufacturing companies

4.2.1 Manufacturing market factor

As can be seen in Table 4, the value-weighted returns of the stocks of manufacturing companies are on average higher than those of the whole economy and of non-manufacturing stocks. However, the correlation of the manufacturing market factor and the whole economy market factor and non-manufacturing market factor is over 90% in both sample periods.

Furthermore, the paired sample t-tests suggest, that the hypothesis that the manufacturing and other market factors have a zero mean difference, cannot be rejected. This is also supported by the fact, that in median terms (unlike in mean) the manufacturing market factor lags behind both whole-economy market factor and non-manufacturing market factor in the sample from 1967 and behind non-manufacturing market variable in the sample from 1992.

Table 4 - Market factor returns summary statistics from 1967 and 1992

	from 1967			from 1992		
	MKT	*MKT_m*	*MKT_nm*	*MKT*	*MKT_m*	*MKT_nm*
Mean	0.56	0.58	0.54	0.68	0.71	0.66
(t-stats)	(3.15)	(3.23)	(3.00)	(2.99)	(3.12)	(2.81)
Median	0.95	0.83	0.96	1.18	1.19	1.23
Sample var.	20.01	20.78	20.61	17.26	17.43	18.56
Kurtosis	1.82	1.88	1.66	1.45	1.09	1.75
Skewness	-0.54	-0.50	-0.52	-0.75	-0.70	-0.77
Minimum	-23.10	-24.42	-21.58	-17.12	-16.21	-17.94
Maximum	16.01	16.22	16.55	11.33	10.32	12.25

Basic statistics are presented for the returns on the market factor constructed from the whole sample (MKT), from manufacturing stocks only (MKT_m), and from non-manufacturing stocks (MKT_nm). There are two sample periods shown, one starting in 1967 in accordance with Hou, Mo, Xue, and Zhang (2019) and the other staring in 1992 based on the requirement of minimum sample size of 8 constituents in each underlying portfolio. The mean, median, variance, minimum and maximum are presented in percentage terms.

Table 5 - Manufacturing market factor correlation from 1967 and 1992

		from 1967		from 1992	
		MKT	*MKT_nm*	*MKT*	*MKT_nm*
MKT_m	correlation	0.98	0.93	0.97	0.91
	p-value	(0.00)	(0.00)	(0.00)	(0.00)
	paired sample t-test	{0.76}	{0.63}	{0.60}	{0.51}

Correlation, p-value of the correlation and the paired sample t-test are exhibited in order to compare the market factor created from the manufacturing stocks only (MKT_m) to the market factor created from the whole sample (MKT) and the market factor constructed from non-manufacturing stocks (MKT_nm).

Unsurprisingly, the difference between the whole-economy, manufacturing, non-manufacturing and HXZ market excess return factor is not all that discernible on the two graphs with indices presented in Figure 8. All four indices seem to co-move almost perfectly, with a bit of spread forming between them starting 2011 onward.

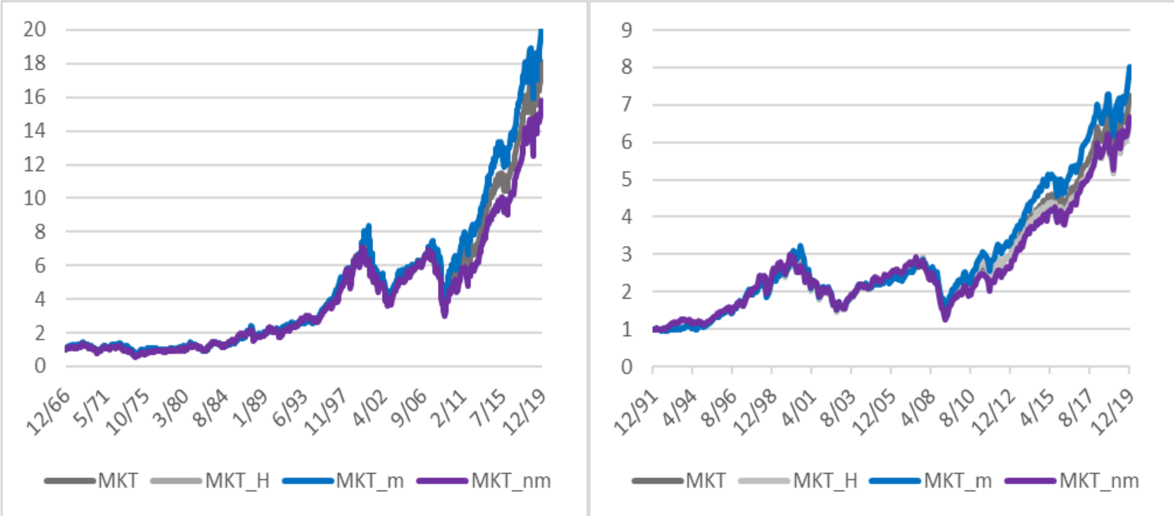

Figure 8 - MKT factors indices with base year 12/1966 and 12/1991

As mentioned before, there is no evidence that manufacturing stocks offer different returns than the rest of the economy. This is in line with the market factor hypothesis that the excess market return factor created from the manufacturing sector stocks only will not be significantly different from the excess market return factor constructed from the whole sample. Based on the paired sample t-tests not being statistically significant, the market factor hypothesis is not rejected.

4.2.2 Manufacturing size factor

The proportions of manufacturing stocks assigned to size groups based on the NYSE median resemble closely the total sample. This can be concluded from Figure 9. However, the size-based groups do not seem to have the same number of constituents. This suggests that the NYSE breakpoints are not representative of all three selected exchanges for the size variable. On average the NYSE stock exchange trades larger firms' stocks (group 2) than NASDAQ and AMEX. This holds true for the manufacturing stocks as well.

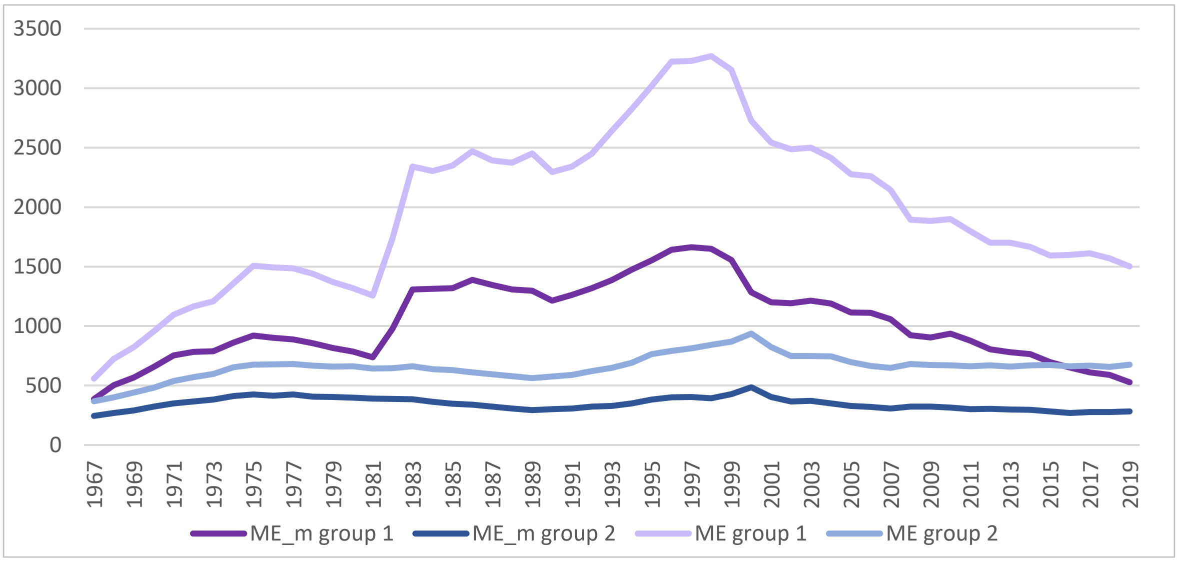

Figure 9 - ME groups sizes

The returns on the ME factor constructed from the manufacturing stocks compared to non-manufacturing stocks factors and the whole sample are shown in Table 6 and Table 7, which summarize the factor returns statistics and correlations.

Interestingly, the ME factor is not statistically significant at any reasonable level for any of the approaches in the sample period 1992-2019, with the t-statistics being only between 1 and 1.3.

The size factor index constructed from manufacturing stocks and the one constructed from non-manufacturing stocks have a correlation of roughly 80% in both of the samples. The paired sample t-test of both sample periods also suggests that the hypothesis that there is no mean difference between manufacturing and non-manufacturing size factor returns is not rejected. The correlations of manufacturing stocks size factor and the size factor based on the whole sample in both sample periods are over 90%.

The ME factor returns are almost the same for the manufacturing and other than manufacturing stocks in the long sample period and higher for the manufacturing stocks in the 1992 sample. The manufacturing stocks size factor is slightly higher than the size factor created from the whole sample in the long and short timeframe. However, none of these differences are statistically significant.

Table 6 - Size factor returns summary statistics from 1967 and 1992

	from 1967			from 1992		
	ME	*ME_m*	*ME_nm*	*ME*	*ME_m*	*ME_nm*
Mean	0.26	0.27	0.27	0.22	0.23	0.16
(t-stats)	-2.18	-2.03	-2.56	1.27	1.22	1
Median	0.15	0.09	0.18	0.14	0.02	0.11
Sample var.	8.92	10.98	6.93	9.93	12.38	8.28
Kurtosis	5.91	5.63	1.99	8.15	7.62	2.1
Skewness	0.6	0.78	0.15	0.87	1.04	0.24
Minimum	-14.71	-14.93	-11.56	-14.71	-14.93	-11.56
Maximum	22.56	24.89	14.23	22.56	24.89	14.23

Basic statistics are presented for the size factor constructed from the whole sample (ME), from manufacturing stocks only (ME_m), and from non-manufacturing stocks (ME_nm). There are two sample periods shown, one starting in 1967 in accordance with Hou, Mo, Xue, and Zhang (2019) and the other staring in 1992 based on the requirement of minimum sample size of 8 constituents in each underlying portfolio. The mean, median, variance, minimum and maximum are presented in percentage terms.

Table 7 - Manufacturing size factor correlation from 1967 and 1992

		from 1967		from 1992	
		ME	*ME_nm*	*ME*	*ME_nm*
ME_m	correlation	0.96	0.79	0.93	0.80
	p-value	(0.00)	(0.00)	(0.00)	(0.00)
	paired sample t-test	{0.21}	{-0.01}	{0.27}	{0.67}

Correlation, p-value of the correlation and the paired sample t-test are exhibited in order to compare the size factor created from the manufacturing stocks only (ME_m) to the size factor created from the whole sample (ME) and the size factor constructed from non-manufacturing stocks (ME_nm).

Graphically the non-manufacturing size factor seems to have higher returns in the longer period, but as was stipulated before, the factors are not statistically significantly different from each other.

For all three approaches the size factor index rose in the first decade of the sample, then it fell in the 1983-1999 period, then rose again sharply in the 2000-2010 period, after which it remained quite stagnant. The size factor index constructed from manufacturing stocks and the one constructed from non-manufacturing stocks diverge and converge during the ’67 sample period. In the shorter timeframe they also seem to co-move significantly.

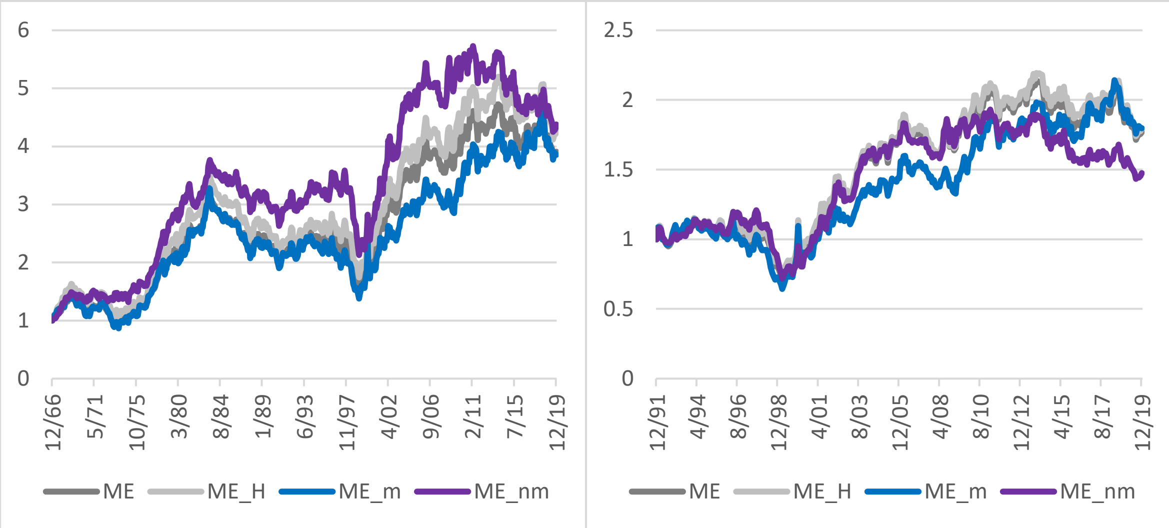

Figure 10 - ME factors indices with base year 12/1966 and 12/1991

All in all, there are no statistically significant differences between the size factors constructed based on sectors. Therefore, the size factor hypothesis, which asserts that size factor constructed on manufacturing stocks will be lower than the size factor created from the other companies, is rejected.

Although the size factor hypothesis states that size factor constructed on manufacturing stocks will be lower than the size factor created from the other companies is rejected, the manufacturing size factor has the highest average return in the 1992 onward period. However, this is not, as was already mentioned, a statistically significant difference. Furthermore, in both the longer and shorter sample it has the lowest median, suggesting that the relatively high mean return is a result of a few highly positive observations.

4.2.3 Manufacturing investment factor

As can be seen from Figure 11, the proportions of manufacturing stocks assigned to investment groups based on the NYSE 30th and 70th percentile resemble closely the total sample. Overall, all three groups seem to be well balanced, having similar number of constituents. This suggests that for the investment variable the NYSE breakpoints are representative of the three selected exchanges.

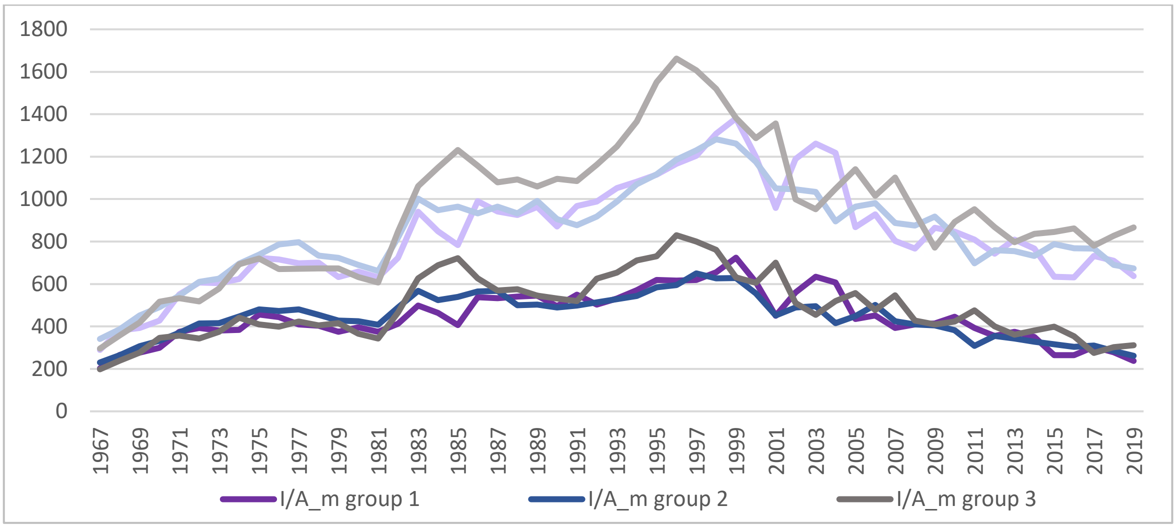

Figure 11 - I/A groups sizes

The investment factor index computed from manufacturing stocks has almost the same returns as the non-manufacturing investment factor during the short sample period. In the long sample period, the mean of returns on the manufacturing investment factor is over 50% higher than that of the non-manufacturing sector investment factor. Furthermore, the manufacturing I/A factor correlation with the non-manufacturing investment factors is about 55%, which is a lower than the correlation of ME factors. This also suggests that the factors are quite distinct.

However, the mean difference between the manufacturing and non-manufacturing stocks falls short of being statistically significant even at 10% level in the long period, with the paired sample t-test being only 1.61. In the short timeframe there is no discernible difference between the manufacturing and non-manufacturing investment factor.

Table 8 - Investment factor returns summary statistics from 1967 and 1992

	from 1967			from 1992		
	I/A	*I/A_m*	*I/A_nm*	*I/A*	*I/A_m*	*I/A_nm*
Mean	0.32	0.38	0.25	0.21	0.22	0.21
(t-stats)	-4.27	-4.57	-2.75	1.93	1.69	1.78
Median	0.3	0.21	0.23	0.17	0.08	0.14
Sample var.	3.48	4.47	5.22	3.83	5.56	4.77
Kurtosis	1.17	1.34	0.84	1.65	1.46	0.73
Skewness	0.14	0.32	-0.02	0.38	0.49	0.2
Minimum	-6.44	-7.3	-7.97	-6.44	-7.3	-7.97
Maximum	9.55	10.02	9.01	9.55	10.02	9.01

Basic statistics are presented for the investment factor constructed from the whole sample (I/A), from manufacturing stocks only (I/A_m), and from non-manufacturing stocks (I/A_nm). There are two sample periods shown, one starting in 1967 in accordance with Hou, Mo, Xue, and Zhang (2019) and the other staring in 1992 based on the requirement of minimum sample size of 8 constituents in each underlying portfolio. The mean, median, variance, minimum and maximum are presented in percentage terms.

Table 9 - Manufacturing investment factor correlation from 1967 and 1992

		from 1967		from 1992	
		I/A	*I/A_nm*	*I/A*	*I/A_nm*
I/A_m	correlation	0.86	0.54	0.86	0.55
	p-value	(0.00)	(0.00)	(0.00)	(0.00)
	paired sample t-test	{1.54}	{1.61}	{0.16}	{0.04}

Correlation, p-value of the correlation and the paired sample t-test are exhibited in order to compare the investment factor created from the manufacturing stocks only (I/A_m) to the investment factor created from the whole sample (I/A) and the investment factor constructed from non-manufacturing stocks (I/A_nm).

The investment factor index computed from manufacturing stocks closely follows the HXZ investment factor index. All the I/A factors are rising or stagnant during the whole sample, with a sharp drop around the early 2000s recession. In the long period sample, the manufacturing and non-manufacturing investment factors diverge significantly, with the non-manufacturing investment factor index quadrupling over the 1967-2019 period and the manufacturing investment factor growing tenfold.

Even though the relationship can be clearly seen in Figure 12, it is not statistically significant. The paired sample t-test is only 1.54 and 1.61 with economy-wide and non-manufacturing investment factor, respectively, which means neither of them reach statistical significance. In the shorter sample spanning from 1992, there is neither statistically significant distinction between the samples, nor a visual one.

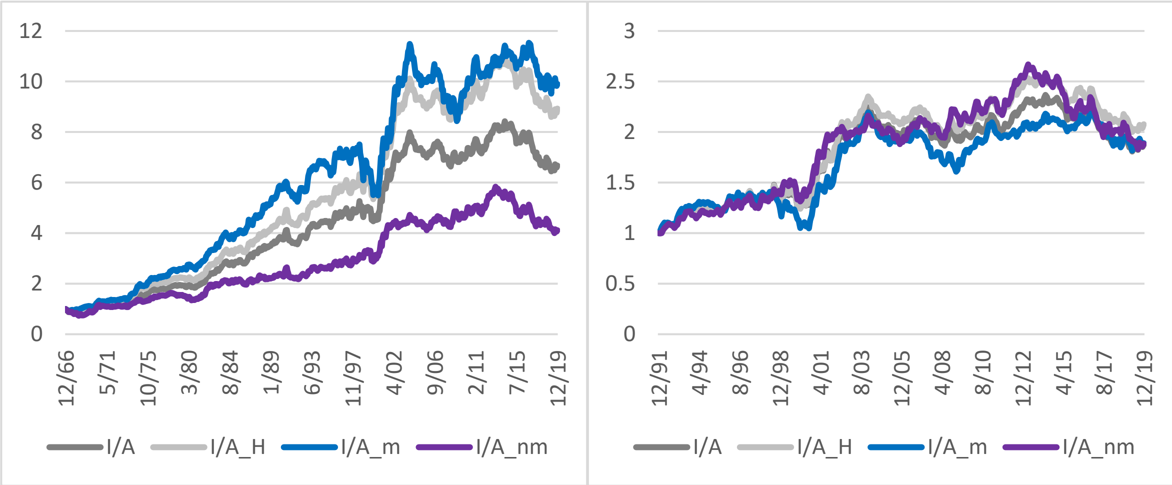

Figure 12 - I/A factors indices with base year 12/1966 and 12/1991

Since none of the paired sample t-tests are statistically significant, the investment factor hypothesis, which states that the manufacturing investment factor will outperform the non-manufacturing investment factor, is rejected.

4.2.4 Manufacturing profitability factor

Figure 13 shows how many stocks are assigned to the different profitability groups based on the NYSE 30th and 70th percentile. The profitability groups from the manufacturing stocks resemble closely the total sample. Overall, all three groups seem to be quite similar in size, especially at the beginning of the sample. From 1983 onwards the high profitability stocks (group 3) have fewer constituents than low profitability stocks (group 1). This indicates that the NYSE stocks are on average a bit more profitable than the stocks traded at AMEX and NASDAQ.

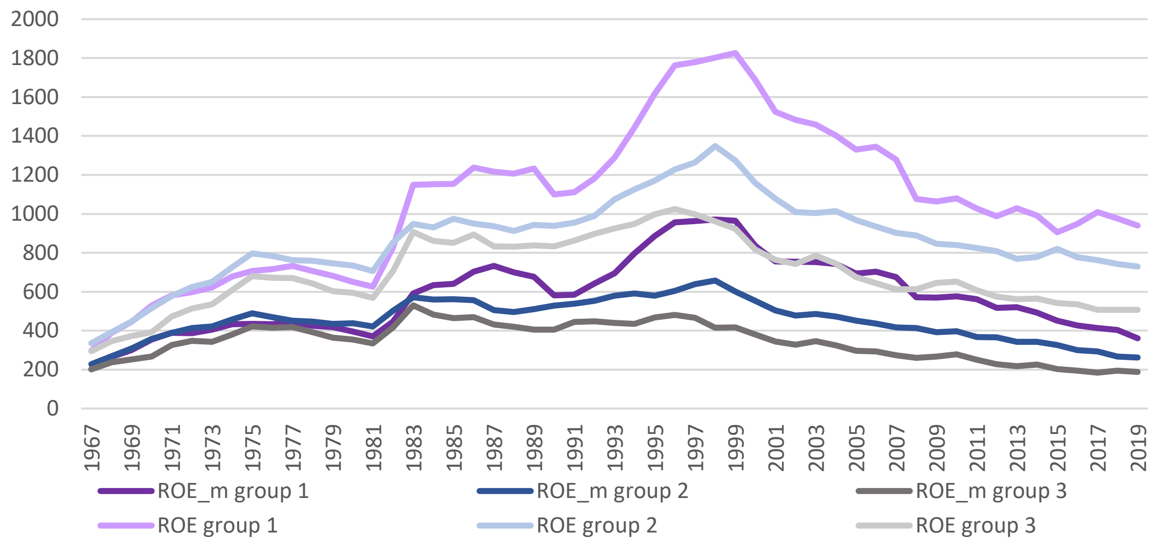

Figure 13 - ROE groups sizes

In the 1992-2019 sample the manufacturing profitability factor returns mean was only 0.29%, while for the non-manufacturing stocks it was double that, 0.59%. With the paired sample t-test of -2.23 the difference between the manufacturing and non-manufacturing ROE factor returns is non-zero at almost 0.025 level.

The means of the ROE indices in the short sample period are all statistically significant except for the manufacturing profitability factor returns, which can be likely attributed to the small sample and relatively lower returns compared to the other ROE factors.

Table 10 - Profitability factor returns summary statistics from 1967 and 1992

	from 1967			from 1992		
	ROE	*ROE_m*	*ROE_nm*	*ROE*	*ROE_m*	*ROE_nm*
Mean	0.54	0.53	0.64	0.4	0.29	0.59
(t-stats)	-5.58	-5.02	-5.89	2.79	1.85	3.75
Median	0.69	0.56	0.72	0.56	0.41	0.67
Sample var.	5.99	7.01	7.57	6.97	8.02	8.4
Kurtosis	4.73	3.86	4.22	4.81	4.04	5.24
Skewness	-0.57	-0.51	-0.51	-0.67	-0.68	-0.65
Minimum	-12.62	-13.58	-15.36	-12.62	-13.58	-15.36
Maximum	10.47	10.86	13.37	9.98	10.58	13.37

Basic statistics are presented for the profitability factor constructed from the whole sample (ROE), from manufacturing stocks only (ROE _m), and from non-manufacturing stocks (ROE _nm). There are two sample periods shown, one starting in 1967 in accordance with Hou, Mo, Xue, and Zhang (2019) and the other staring in 1992 based on the requirement of minimum sample size of 8 constituents in each underlying portfolio. The mean, median, variance, minimum and maximum are presented in percentage terms.

Table 11 - Manufacturing profitability factor correlation from 1967 and 1992

		from 1967		from 1992	
		ROE	*ROE_nm*	*ROE*	*ROE_nm*
ROE_m	correlation	0.88	0.59	0.89	0.61
	p-value	(0.00)	(0.00)	(0.00)	(0.00)
	paired sample t-test	{-0.29}	{-1.19}	{-1.49}	{-2.23}

Correlation, p-value of the correlation and the paired sample t-test are exhibited in order to compare the profitability factor created from the manufacturing stocks only (ROE _m) to the profitability factor created from the whole sample (ROE) and the profitability factor constructed from non-manufacturing stocks (ROE_nm).

The correlation between the profitability factors from manufacturing and non-manufacturing stocks is around 60%. Prior to 1992, the beginning of the shortened sample the factors seem to co-move perfectly. From 1992 to 2019 the non-manufacturing profitability factor index grew sharper than the manufacturing factor index and over that period became three times higher than the manufacturing ROE index factor.

Overall, the manufacturing ROE factor indices grew during the sample period and over sample periods there were two significant peaks and crashes, one in 2008 and another one in 2015. These line up with the 2008 financial crisis and the 2015-16 stock market selloff.

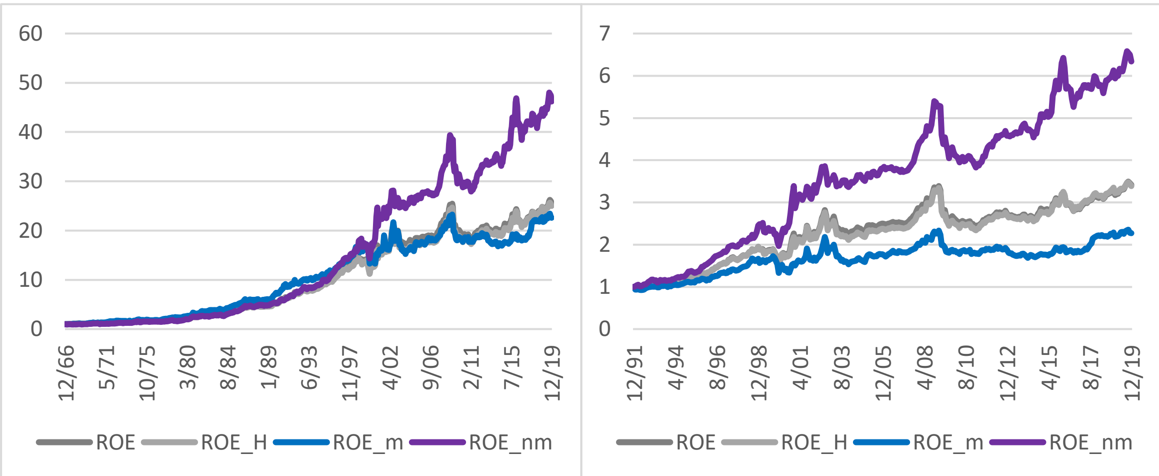

Figure 14 - ROE factors indices with base year 12/1966 and 12/1991

Out of the four factors, only ROE factor is significantly different based on the constituent industry constraints. The ROE factor constructed from manufacturing stocks yields lower returns to those constructed from non-manufacturing or all stocks. This difference is statistically significant in the case of non-manufacturing in the short sample. That is in line with the hypothesis, that the manufacturing profitability factor will yield lower returns compared to non-manufacturing sectors profitability factor. Based on the short sample the profitability factor hypothesis is therefore not rejected.

5 Discussion

5.1 Market factor

Currently there are no prominent studies that would provide a rationale for difference in value weighted returns on manufacturing sector as opposed to the whole economy. That is also in line with the empirical findings presented herein. The split between the manufacturing stocks excess market return factor and the excess returns on the rest of the economy is not statistically significant. This holds true for both sample periods and therefore the market factor hypothesis is not rejected.

The difference between the manufacturing market factor and the market factor created from the stocks of non-manufacturing companies is negligible during the whole timeframe and at no point during the sample periods is there a significant deviation. Since the hypothesis seems to hold for both samples and there are no discrepancies between the theory and empirical findings, the results presented in the section 4.2.1 do not warrant any further examination.

5.2 Size factor

Similarly to the manufacturing market factor, there is currently a lack of literature that would differentiate the size factor returns based on economic sector from which this factor is created, more precisely based on the manufacturing sector. That likely has to do with the fact that there seems to be no empirical relationship between stocks from manufacturing sector and the size factor.

Interestingly enough, none of the size factors are even statistically significant at any reasonable level. This puts the very existence of the size factor constructed based in HXZ (2015) methodology into question, at least during the analysed sample periods. It is also in line with Hou, Xue, and Zhang (2012) conclusion, that they only included "*the size factor primarily to reduce the average magnitude of the alphas across size-related portfolios. As such, the size factor plays only a secondary role in the q-factor model, whereas the investment and the ROE factors are more prominent*" (HXZ, 2012, pg. 3).

The hypothesis for the size factor was created based on the observation, that the manufacturing firms have smaller share of employees in small businesses. The hypothesis is that the size factor created from the manufacturing sector stocks only is lower than the size factor constructed from the rest of the economy. This hypothesis is rejected as there is no significant difference found between the size factor created solely from manufacturing sector stocks and the other size factors, i.e., the size factor created from non-manufacturing stocks and the size factor created from all stocks. Moreover, the results have a different direction than anticipated, with the manufacturing size factor having higher returns rather than lower.

Since there seems to be no difference between the size factors constructed from different sector stocks, it is questionable whether this is subject worthwhile pursuing any further. This seems even more questionable due to the fact that the lack of relation between manufacturing stocks and size factor is even more pronounced in the longer sample period.

One size-factor related area where a further research could be helpful, is in searching for a more solid theoretical background for the manufacturing size factor hypothesis. Another one, perhaps more important, is conclusively determining the very existence of the size factor and the role of underlying portfolios used in factor construction.

5.3 Investment factor

The investment factor hypothesis that the manufacturing investment factor will be higher than the investment factor from the rest of the economy was rejected. However, the results were close to being statistically significant at 10% level for the longer sample.

The main, short, sample period yielded results that were consistent with the conclusion that selection of sector does not influence the investment factor returns. This suggests the 1967-1991 period results are in line with the hypothesis and the 1992-2019 period results are not, showing very little difference between the manufacturing and non-manufacturing size factors.

There are two main questions that arise from these results presented in subsection 4.2.3. The first one is whether there actually is a difference between the investment factor constructed from the manufacturing stocks as opposed to stocks from the rest of the economy and it just has not been found due to the length of the sample period. The answer to this question can be determined once more out-of-sample data is available.

The second question is what makes the 1967-1991 period different from the 1992-2019 in terms of the manufacturing investment factor performance. In the first part of the 1967-2019 sample period the difference between the manufacturing investment factor and the other investment factors is easily discernible. In the later years, the investment factors seem to comove almost perfectly. Whether there is some reason behind this behaviour or it is due to chance remains to be explored.

5.4 Profitability factor

The profitability factor hypothesis that the manufacturing sector profitability factor will yield lower returns than the profitability factor created from non-manufacturing stocks is not rejected in the short timeframe, with the paired sample t-test being 2.23.

However, the hypothesis does not pass the robustness check, since the paired sampled t-test of the longer period is only 1.19. Therefore, the hypothesis not being rejected could simply be a result of the period restriction, since in the 1967-2019 period the paired sample t-test shows that the hypothesis that the means of the profitability factors returns are the same cannot be rejected. Even visually until 1992 the manufacturing profitability factor seems to comove perfectly with the other profitability factors. In order to ascertain whether there indeed is a prevalent disparity between the ROE factors or this was a relationship specific to the short sample period only, more out-of-sample data will be needed.

Furthermore, the same relationship is not statistically significant when comparing manufacturing profitability factor with whole-economy profitability factor. That is partially to be expected, because manufacturing sector plays a significant role in the economy. However, finding a difference between manufacturing profitability factor and the basic profitability factor would make the findings much more robust. To that end, more data points would be helpful in determining whether the manufacturing ROE factor is statistically significantly different from the ROE factor constructed from all industries.

5.5 Q-factor model

Despite its many advantages, the q-factor model has one major drawback that might render it unusable in future and already does now in some parts of the world. That is the fact that it needs quarterly fundamentals data to construct the profitability factor, which is arguably the most important factor of all the q-factors.

The need for quarterly fundamentals data is an obstacle to use of q-factor model in many countries. EU countries are a prime example, with only semi-annual financial reports being required by the transparency directive (2004/109/EC). Although a large number of European firms do provide their financial reports quarterly (Lannoo and Khachaturyan, 2003, Table 1), many do not. Since the quarterly financial reporting is not obligatory for all listed companies, the creation of q-factors just based on the companies that report quarterly voluntarily could lead to difficulties. Chief among them would likely be sample selection biases and insufficient number of companies in the sample for q-factors construction. The former one could be especially problematic if there are some common characteristics among the companies that choose to do the extra reporting or those that do not, this could lead to distortion of the results.

However, the EU is by no means the only region where the q-factor model is not usable in its current form. Even in the US there has recently also been a debate about reducing the frequency of reporting (Reuters, 2018), which would make the q-factor model obsolete. However, at the moment there do not seem to be any strong pushes in that direction, so in the US the q-factor model lives to see another day.

6 Conclusions

The aim of this paper was to assess whether the q-factor model proposed by Hou, Xue, and Zhang (2015) would behave differently when constructed solely on manufacturing stocks, as opposed to the whole economy and non-manufacturing stocks. The results provide some evidence that there indeed are some differences, but the evidence is very limited.

The paired sample t-test was used for the purpose of assessing the difference between the factors' returns. Whenever the t-test yielded high enough values to reject the hypothesis that the means of the two samples are the same, that meant that the factors created from the different economy sectors are significantly different.

Using the paired sample t-test, this paper found that three of the four manufacturing factors were indistinguishable from their non-manufacturing counterparts. These were the market factor, the size factor, and the profitability factor. The manufacturing profitability factor was significantly lower than that constructed from non-manufacturing stocks in the sample period. However, this significance did not persist in the longer sample, which served as a robustness check, as it could not be used as the main sample due to insufficient number of manufacturing companies in some of the sample periods.

The observation that the manufacturing excess market return factor is not statistically significantly different from the non-manufacturing stocks market factor was in line with the market factor hypothesis which predicted this outcome. The hypothesis was constructed based on the lack of literature suggesting a different outcome and comparison of the market indices and industrials indices (Figure 2 and Figure 3).

The size factor hypothesis stated that the size factor created from the manufacturing sector stocks would have lower returns than the size factor created from non-manufacturing stocks. This hypothesis was rejected, because the results did not show any differences among the factors in the short period, or in the longer, validation, period. Interestingly, in the longer validation period the return on the manufacturing sector size factor actually had higher average returns than the returns on the size factor created from non-manufacturing stocks, which is contrary to the hypothesis. However, the longer period has low number of constituents of the underlying portfolios and the factors are therefore more prone to the effect of outliers in the 1967-1991 period. Furthermore, the results are not statistically significant, which makes these observations regarding the manufacturing size factor having higher returns inconclusive.

The investment factor hypothesis was built on the fact than leverage is positively correlated with financial constraints (Fernando and Mulier, 2015) and this in turn is negatively correlated with investment (Hou, Xue, and Zhang, 2015). The leverage levels vary more among the manufacturing firms than they did among non-manufacturing firms (Bernanke et al., 1990). Based on that the investment factor hypothesis proposed that the investment factor returns will be higher for the manufacturing sector than for the non-manufacturing stocks.

The investment factor hypothesis is rejected in the short sample, because the paired sample t-test is close to 0. However, in the longer period the paired sample t-test is 1.61, so not too far away from being significant at 10% level. The large discrepancy between the t-statistics in the short sample and the long sample is interesting and is well illustrated in the visualization of the indices of the investment factors (Figure 12). This thesis does not make an attempt to explain the difference in the behaviour of the investment factors during the 1967-1991 and 1992-2019 periods, since the hypothesis is rejected regardless. However, the fact that the difference between the manufacturing investment factor and non-manufacturing investment factor seemingly disappears around 1992 provides an interesting avenue for further research.

The profitability factor provides the most interesting results out of all the q-factors. The hypothesis that the manufacturing profitability factor will provide lower returns than the profitability factor constructed from non-manufacturing stocks is not rejected, because the paired sample t-test is 2.23 in the shorter sample period.

The profitability hypothesis is based on paper by Baker (1973), which introduced a model showing that leverage and profitability are positively correlated, and on the fact that on average the manufacturing sector stocks have historically had lower leverage (Bernanke et al., 1990). This is also supported by an observation made by Lifschutz (2019) who found that manufacturing sector has relatively low profitability. Furthermore, the data in Ready Ratios ([45]), which provides the gross margin medians by industry, suggests that profitability ranges are significantly lower for the manufacturing sector industries compared to rest of the economy.

However, even though the profitability hypothesis is not rejected in the short sample period, it does not pass the robustness check that is the longer sample. Here the paired sample t-test score is only 1.19. As mentioned before, this could be caused by the low number of constituents in the underlying portfolios, which could give undue weight to outliers. However, even if that is the case, currently the manufacturing profitability factor findings lack the robustness to state with certainty that the manufacturing profitability factor is lower than the non-manufacturing profitability factor.

This poses an interesting topic for further research, once out-of-sample data becomes available. An alternative research topic stemming from the profitability factor hypothesis failing the robustness check is a deep dive into what is the underlying reason for the difference in the relative performance of the profitability factors in the 1967-1991 and 1992-2019 periods.

All in all, the assessment of the difference of the US manufacturing sector and the rest of the economy in terms of q-factors is an interesting research topic, which yielded mostly inconclusive results. However, these results are worth further investigation. That is especially true in the case of the investment and profitability factors. This research will, however, most likely have to be put on hold until more data is available for further analyses.

References

[1] Baker, S.H., 1973. Risk, leverage and profitability: an industry analysis. *The Review of Economics and Statistics*, pp.503-507.

[2] Banz, R.W., 1981. The relationship between return and market value of common stocks. *Journal of financial economics*, 9(1), pp.3-18.

[3] Barillas, F. and Shanken, J., 2018. Comparing asset pricing models. *The Journal of Finance*, 73(2), pp.715-754.

[4] Beaver, W., McNichols, M. and Price, R., 2007. Delisting returns and their effect on accounting-based market anomalies. *Journal of Accounting and Economics*, 43(2-3), pp.341-368.

[5] Berk, J.B., Green, R.C. and Naik, V., 1999. Optimal investment, growth options, and security returns. *The Journal of finance*, 54(5), pp.1553-1607.

[6] Bernanke, B.S., Campbell, J.Y., Whited, T.M. and Warshawsky, M., 1990. US corporate leverage: Developments in 1987 and 1988. *Brookings Papers on Economic Activity*, 1990(1), pp.255-286.

[7] Carhart, M.M., 1997. On persistence in mutual fund performance. *The Journal of finance*, 52(1), pp.57-82.

[8] Cooper, M.J., Gulen, H. and Schill, M.J., 2008. Asset growth and the cross-section of stock returns. *the Journal of Finance*, 63(4), pp.1609-1651.

[9] Crain, M.A., 2011. A literature review of the size effect. Available at: *SSRN* 1710076.

[10] CRSP U.S. Stocks & Indices Data Descriptions, WRDS. Available at*: https://wrds-www.wharton.upenn.edu/pages/support/manuals-and-overviews/crsp/stocks-and-indices/overview-crsp-us-stock-database*. [Accessed Aug. 1, 2020]

[11] CRSP/Compustat Merged Database - Fundamentals Quarterly – Variable Description, WRDS. Available at: *https://wrds-web.wharton.upenn.edu/wrds/ds/crsp/ccm_a/fundq/index.cfm?navId=120* [Accessed Oct. 25, 2020]

[12] Daniel, K., Hirshleifer, D. and Sun, L., 2020. Short-and long-horizon behavioral factors. *The Review of Financial Studies*, 33(4), pp.1673-1736.

[13] De Bondt, W.F. and Thaler, R., 1985. Does the stock market overreact?. *The Journal of finance*, 40(3), pp.793-805.

[14] Fama, E.F. and French, K.R., 1992. The cross-section of expected stock returns. *The Journal of Finance*, 47(2), pp.427-465.

[15] Fama, Eugene F., and Kenneth R. French, 1993, Common risk factors in the returns on stocks and bonds, *Journal of Financial Economics,* 33, pp. 3–56.

[16] Fama, E.F. and French, K.R., 2004. The capital asset pricing model: Theory and evidence. *Journal of economic perspectives*, 18(3), pp.25-46.

[17] Fama, E.F. and French, K.R., 2015. A five-factor asset pricing model. *Journal of financial economics*, 116(1), pp.1-22.

[18] Fama, E.F. and French, K.R., 2018. Choosing factors. *Journal of financial economics*, 128(2), pp.234-252.

[19] Ferrando, Annalisa & Mulier, Klaas. (2015). Firms' Financing Constraints: Do Perceptions Match the Actual Situation?. Economic and Social Review. 46.

[20] French, Kenneth R. – Data Library, Kenneth R. French. Available at: *https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/Data_Library/f-f_5_factors_2x3.html* [Accessed Nov. 10, 2020]

[21] George, T.J., Hwang, C.Y. and Li, Y., 2018. The 52-week high, q-theory, and the cross section of stock returns. *Journal of Financial Economics*, 128(1), pp.148-163.

[22] Gibbons, M.R., Ross, S.A. and Shanken, J., 1989. A test of the efficiency of a given portfolio. *Econometrica: Journal of the Econometric Society*, pp.1121-1152.

[23] Harvey, C.R., Liu, Y. and Zhu, H., 2016. … and the cross-section of expected returns. *The Review of Financial Studies*, 29(1), pp.5-68.

[24] Hou, K., Xue, C. and Zhang, L., 2012. Digesting anomalies: An investment approach. *NBER working paper series*.

[25] Hou, K., Xue, C. and Zhang, L., 2014. A comparison of new factor models (No. w20682). *National Bureau of Economic Research*.

[26] Hou, K., Xue, C. and Zhang, L., 2015. Digesting anomalies: An investment approach. *The Review of Financial Studies*, 28(3), pp.650-705.

[27] Hou, K., Xue, C. and Zhang, L., 2017a. A comparison of new factor models. *Fisher College of Business Working Paper*, (2015-03), p.05.

[28] Hou, K., Xue, C. and Zhang, L., 2017b. Replicating anomalies (No. w23394). *National Bureau of Economic Research*.

[29] Hou, K., Mo, H., Xue, C. and Zhang, L., 2017. The economics of value investing (No. w23563). *National Bureau of Economic Research*.

[30] Hou, K., Mo, H., Xue, C. and Zhang, L., 2018. Motivating factors. *SSRN eLibrary*.

[31] Hou, K., Mo, H., Xue, C. and Zhang, L., 2019. Which factors?. *Review of Finance*, 23(1), pp.1-35.

[32] Hou, K., Mo, H., Xue, C. and Zhang, L., 2020a. An augmented q-factor model with expected growth. *Review of Finance*.

[33] Hou, K., Mo, H., Xue, C. and Zhang, L., 2020b. Q-factor model factors database. Available at: *http://global-q.org/factors.html* [Accessed 8 Nov. 2020].

[34] Jegadeesh, N. and Titman, S., 1993. Returns to buying winners and selling losers: Implications for stock market efficiency. *The Journal of finance*, 48(1), pp.65-91.

[35] Keim, D.B., 1983. Size-related anomalies and stock return seasonality: Further empirical evidence. *Journal of financial economics*, 12(1), pp.13-32.

[36] Klein, R.W. and Bawa, V.S., 1977. The effect of limited information and estimation risk on optimal portfolio diversification. *Journal of Financial Economics*, 5(1), pp.89-111.

[37] Lannoo, K. and Khachaturyan, A., 2003. Disclosure Regulation in the EU: the emerging framework. *CEPS Task Force Reports No. 48*, 1 October 2003.

[38] Lifschutz, M., 2019. Top 10 Most Profitable US Industries. Available at: *https://www.ibisworld.com/industry-insider/analyst-insights/top-10-most-profitable-us-industries/.* [Accessed 17 Jan. 2021]

[39] Lintner, J., 1965. Security prices, risk, and maximal gains from diversification. *The journal of finance*, 20(4), pp.587-615.

[40] Markowitz, H., 1952. The utility of wealth. *Journal of political Economy*, 60(2), pp.151-158.

[41] Mossin, J., 1966. Equilibrium in a capital asset market. Econometrica: *Journal of the econometric society*, pp.768-783.

[42] Novy-Marx, R., 2013. The other side of value: The gross profitability premium. *Journal of Financial Economics*, 108(1), pp.1-28.

[43] Overview of CRSP U.S. Stock Database, WRDS. Available at: *https://wrds-www.wharton.upenn.edu/pages/support/manuals-and-overviews/crsp/stocks-and-indices/overview-crsp-us-stock-database*. [Accessed Aug. 1, 2020]

[44] Pizzola, B., 2018. Business regulation and business investment: evidence from US manufacturing 1970–2009. *Journal of Regulatory Economics*, 53(3), pp.243-255.

[45] Ready Ratios, 2019. Gross margin – breakdown by industry. Available at: *https://www.readyratios.com/sec/ratio/gross-margin/.* [Accessed Jan. 17, 2021]

[46] Reuters, 2018. Trump's pitch to end quarterly reports would follow EU, Australia. Available at: *https://www.reuters.com/article/us-usa-sec-trump-factbox-idUSKCN1L51ZN*

[47] Roll, R., 1983. Vas ist Das? The turn-of-the-year effect and the return premia of small firms, *Journal of Portfolio Management*, 9, 18-28.

[48] Sharpe, W.F., 1964. Capital asset prices: A theory of market equilibrium under conditions of risk. *The journal of finance*, 19(3), pp.425-442.

[49] SIC codes industries, NAICS. Available at: *https://www.naics.com/sic-codes-industry-drilldown/.* [Accessed Aug. 25, 2020]

[50] Sigman, K., 2005. Capital Asset Pricing Model (CAPM) [Lecture notes]. *Columbia University*. Available at: *https://www.columbia.edu/~ks20/FE-Notes/4700-07-Notes-CAPM.pdf.* [Accessed Dec. 25, 2020]

[51] Stambaugh, R.F. and Yuan, Y., 2017. Mispricing factors. *The Review of Financial Studies*, 30(4), pp.1270-1315.

[52] Statista: Duffin, E., 2020. Percentage added to the Gross Domestic Product (GDP) of the United States of America in 2019, by industry. Available at:

https://www.statista.com/statistics/248004/percentage-added-to-the-us-gdp-by-industry/ [Accessed 9 Jan. 2021].

[53] Suominen, M., 2019. Investment and portfolio choice in discrete time [Slides]. *Aalto University.* Available at: *https://mycourses.aalto.fi/pluginfile.php/932099/mod_resource/content/1/Lecture%201%20AIT%202019.pdf.* [Accessed Dec. 25, 2020]

[54] The Office of Advocacy of the U.S. Small Business Administration, 2018. United States Small Business Profile, 2018. Available at: *https://www.sba.gov/sites/default/files/advocacy/2018-Small-Business-Profiles-US.pdf.* [Accessed 17 Jan. 2021].

[55] Thomas, D.S., National Institute of Standards and Technology, U.S. Department of Commerce, 2012. The Current State And Recent Trends Of The U.S. Manufacturing Industry. *NIST Special Publication 1142*.

[56] Treynor, J.L., 1961. Market value, time, and risk. Time, and Risk. Unpublished manuscript dated August 8, 1961.

[57] Urbański, S., Jawor, P. and Urbański, K., 2014. The impact of penny stocks on the pricing of companies listed on the Warsaw Stock Exchange in light of the CAPM. *Folia Oeconomica Stetinensia*, 14(2), pp.163-178.

[58] Yuskavage, R.E. and Pho, Y.H., 2004. Gross Domestic Product by Industry for 1987-2000. *Survey of Current Business*, pp.33-53.

[59] Yuskavage, R.E. and Fahim-Nader, M., 2005. Gross Domestic Product by Industry for 1947-86. *Survey of Current Business*, December, pp.70-84.

A. Constraints for CCMA and CCMQ database

Constraints placed on the data downloaded from the CCMA and the CCMQ database are:

- The linktype selected was Lc and Lu, i.e., where link research is complete – there is match in CUSIP number and price, and where link is established through comparison of historical CUSIP number.
- Consolidated data was used.
- The industry format was indl.
- The selected data format was STD.
- The population source was D.
- The chosen currency was USD.
- Active and inactive companies were selected.

B. Delisting adjustment

Delisting file is first downloaded from the CRSP databases. Since no payment date in the file comes before delisting date, there is no need to deal with delisting return data containing only partial month returns.

There are multiple approaches to dealing with delisting returns, based on what data are contained in the variables the DLRET (delisting return) and RET (return). The approaches are presented below.

First, for the observations which have the DLRET and the RET variables available, these variables stay as they are. Since that means, the delisting happened on the last day of the month and therefore will be used in the month following the delisting.

Second, the observations that have ‘na’ value in RET variable and numerical value in the DLRET variable will shift the DLRET value to the RET variable. That is because it for these observations DLRET contains partial month returns and delisting return.

Third, when DLRET is not ‘na’ value, but is not a float value either and the RET value is ‘na’, the RET can be calculated by compounding the returns from the CRSP daily returns database. The DLRET is then taken as the median of DLRETs with the same delisting reason over the past 5 years.

Fourth, the observations that have a non-numeric value and are not ‘na’ in the DLRET variable and have a float number in RET variable will have the DLRET approximated in the same way as mentioned in the previous paragraph, i.e. by taking the median of previous 5 years’ DLRETs with the same delisting reason.

Lastly, the observations with no lagprice are deleted.

After making these adjustments to the data, the monthly stock returns are adjusted “*by compounding returns in the month before delisting with delisting returns*” (Hou, Xue, and Zhang, 2017b, pg.127).