Investment patterns of innovation-efficient firms

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Abstract- The innovation efficiency of firms can be investigated with the help of various methods and data sets. The starting point of this study is an innovation efficiency score based on Data Envelopment Analysis. In general, it is interesting to determine which characteristics innovation-efficient and non-innovation-efficient firms show regarding investment activities in innovations. In addition, their characteristics in terms of firm performance and firm valuation are also of interest. The paper aims to identify the investment patterns of innovation-efficient firms in contrast to non-innovation-efficient ones. A period from 2007 to 2017 is considered to identify these characteristics. Innovation-efficient firms show superior performance in terms of valuation and financial indicators. Investing into innovation efficiency leads to a better future for firms: Innovation efficient firms stay ahead of their competitors due to their steady investment into innovation activities.
Keywords – Innovation efficiency; investment patterns; times series; innovation capability; firm performance

I. INTRODUCTION

A firm's capability to generate innovations is one of the key activities to gain competitive advantage (Hagström et al., 1999; Ngo and O'Cass, 2013). The innovation capability allows firms to respond quickly to changing markets and customer needs and hence generate innovation-driven growth (Yang et al., 2015). The innovation capability consists of innovation input factors and output factors. Innovation input factors describe the essential tangible and intangible resources that are used to generate innovations. Innovation output factors describe the extent of realised product, service, process or business model innovations (Bayrle and Brecht, 2018a). One possibility to measure innovation capability of firms is the evaluation of the innovation process in terms of its efficiency. The so-called innovation efficiency can be understood as the ratio between innovation output and input, based on the idea that a high efficiency is beneficial.

II. PROBLEM IDENTIFICATION AND BASIC PRINCIPLE

Kauffeldt et al. (2012) presented a measure called Return on Innovation, which is calculated by Data Envelopment Analysis (DEA) and compares the innovation efficiency of different firms. This measure was validated within the PhD thesis of Kauffeldt (2014) and represents different input and output dimensions of an innovation process such as R&D investments, innovation culture, knowledge creation, cooperation, commercialization, intellectual property and process changes (Kauffeldt et al., 2012). These variables are in accordance to the different innovation dimensions of the (Oslo Manual, 2005) and other publications (Kilic et al., 2015). For this reason, it is possible to use the Return on Innovation to examine the innovation efficiency of different firms as a valid and objective measuring instrument. Furthermore, understanding and quantifying the resulting implications of the Return on Innovation is very important. The examination of the investment patterns of innovation-efficient firms is of utmost interest. The comparison with non-innovation-efficient firms and their investment behaviour should provide interesting insights. The relationship between innovation-efficient firms and their firm performance is another important perspective. Others have tried to establish a link between innovation performance and firm performance as well (Avermaete et al., 2004; Prajogo, 2016), but failed to distinguish between top and low performer in terms of innovation. This may explain why innovation-efficient firms are so efficient.

The innovation capability is generally regarded as a driver for firm performance (Bayrle and Brecht, 2018b; Bowen et al., 2010; Cruz-Cázares et al., 2013) and thus also for a high market valuation (Hirshleifer et al., 2013). Firms with a high innovation capability can rapidly adapt to changing markets and customer expectations and thus achieve innovation-driven growth (Yang et al., 2015). Several researchers reported innovation capability as multi-faceted construct, including technological innovation, organizational innovation, process innovation and more (Hagström et al., 1999; Lin et al., 2010; Yuan et al., 2016). One way to quantify the innovation capability is to assess the transformation of limited innovation resources through the use of innovation capabilities into desired innovation outputs (Cruz-Cázares et al., 2013). The so called innovation efficiency is based on the concept of productivity, which means that innovation efficiency is improved if the same amount of innovation input generates more innovation output or when less input is used to produce the same innovation output (Almeida et al., 2013; Chen and Guan, 2012; Hirshleifer et al., 2013). Drake et al. (2015) showed that innovation leaders have demonstrated a consistent capability to generate sustainable competitive advantage and superior firm performance through their focus on innovation. Hirshleifer et al. (2013) reported that innovation efficiency could be a useful input for firm valuation. They found that firms that are more innovation-efficient on average have higher market valuations, superior future operating performance, and stock returns. Basse Mama (2018) showed that investing in innovation-efficient firms results in higher returns than investing in non-innovation-efficient firms. The author used an innovation efficiency measure based on patent data and R&D expenditures. Rubera and Kirca (2012) showed that in terms of innovation larger firms appropriate greater returns in terms of market and financial positions, smaller firms are in a better position to benefit from their innovation activities in stock markets. Cruz-Cázares et al. (2013) measured technological innovation efficiency by DEA and a Malmquist Index, they concluded if a firm used an efficient technological innovation process it reached a higher performance. With their results, they showed that an efficient usage of innovation inputs and its transformation into innovation outputs increases firm performance (Kauffeldt et al., 2012). The questions if innovation today leads to superior performance tomorrow or if past firm drives innovation performance is quite challenging. Bowen et al. (2010) addressed these questions within a meta-analysis. They found support for their first hypothesis that innovation and future performance are positive related. Most challenging is to answer if past firm performance fosters or reduces future innovation activities. In addition, researchers should pay attention to the time periods of their data. New research insights into the performance and innovation relationships of firms can be gained through appropriate time sequencing.

III. METHODOLOGY

In order to identify the investment patterns of these firms, variables to answer the research questions are needed. The first variable is the annual sales growth rate, which is a good proxy for firm performance, although one has to consider possible limitations due to short-term growth drivers other than innovation (Drake et al., 2015). The second variable is the annual R&D expenditures growth rate, which is correlated with firm growth over a longer time horizon (Demirel and Mazzucato, 2012). R&D Intensity is not used due to comparison issues of this variable (Drake et al., 2015). As value drivers and valuation variables, the EBITDA growth rate, Return on Invested Capital (ROIC) and Enterprise Vale to 12 months EBITDA (EV/EBTIDA) are chosen (Koller and Copeland, 2011).

To evaluate the hypothesis, appropriate variables and a suitable method are needed. The sales growth of the firms can be chosen as an indicator for an economic swing. R&D growth is selected as a proxy for the investments of firms in innovation. In this sample, the period of economic slowdown in 2009, 2013 and 2014 is determined by the sales development of the non-innovation-efficient firms (see Figure 4). The linear relationships between sales growth and R&D growth are determined for the economic periods of upswing and slowdown. These relationships are used to determine whether firms change their R&D policies in the event of economic difficulties. If, during an economic slowdown, innovation-efficient firms reduce their R&D expenditures in a linear ratio to annual sales growth, this can be taken as a measure to reject the hypothesis. At the same time, non-innovation-efficient firms should not only show negative sales growth during an economic slowdown but should also show a decline in R&D expenditures in a verifiable dependency. In total, there are four linear regressions to assess the hypothesis.

During an economic upswing:

1. Relationship between R&D expenditures and sales growth
    a. of innovation-efficient firms
    b. of non-innovation-efficient firms.

During an economic slowdown:

2. Relationship between R&D expenditures and sales growth
    a. of innovation-efficient firms
    b. of non-innovation-efficient firms.

Each year, the 30 innovation-efficient firms and the 30 non-innovation-efficient firms were calculated with the method of Kauffeldt et al. (2012). Data was provided by ALPORA AG and Bloomberg. In order to analyze the investment patterns of the firms, all firms that have been classified as efficient or non-efficient firms for several years, were counted once.

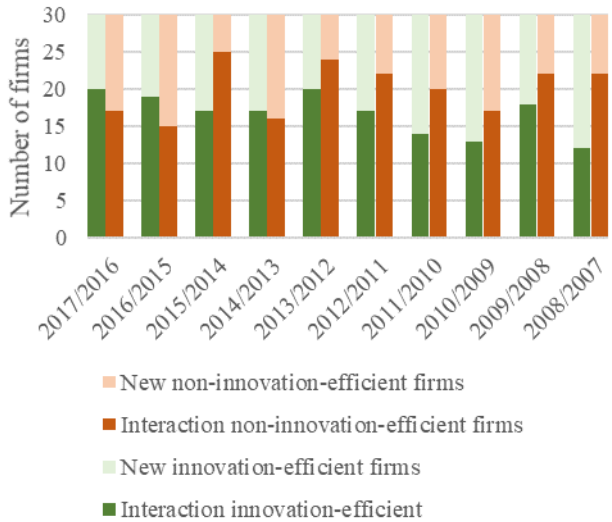

Figure 1. Interaction of innovation-efficient and non-innovation-efficient firms based on a two-year comparison.

So only, the intersections of efficient and non-efficient firms were used. This means that an innovation-efficient firm, which for example was rated as efficient and was in the top 30 innovation-efficient firms in four years, was only counted once. Over an eleven-year period, 97 non-innovation-efficient firms and 122 innovation-efficient firms were identified. Figure 1 shows the development of the innovation-efficient and non-innovation-efficient firms in a two-year comparison. For example, if a firm was listed both times in the top 30 innovation-efficient firms in 2016 and 2017, it is included in Figure 1 in the dark green pillar 2016/2017. 67 firms were industrials, 39 in the consumer-non-cyclical sector, 32 in the consumer-cyclical sector, 28 were technology firms, 19 in basic materials, 17 in the energy sector, 15 in communications, and 2 were in the financial sector. The average market capitalization of the innovation-efficient firms over the 11 years was 10,067 MM € (median 872 MM €) and of the non-innovation-efficient firms 15,786 MM € (median 6,808 MM €).

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IV. RESULTS AND DISCUSSION

Evidently, innovation-efficient firms tended to be smaller than non-efficient firms in terms of market capitalization (see chapter 4) and annual sales. That could be due to the agility of smaller firms, more on this in the following chapter. The median annual sales of the 122 innovation-efficient firms was 585 MM € and of the non-innovation-efficient firms was 8,649 MM €.

The median of the innovation-efficient firms in terms of annual sales growth was 8.14% versus 3.58% of non-efficient firms (see Figure 2). Looking at the median annual R&D expenditure growth there was a similar pattern, 7.32% for innovation-efficient firms versus 4.21% for non-innovation-efficient firms. The temporal evolution of the variables sales growth and R&D growth is shown in Figure 4.

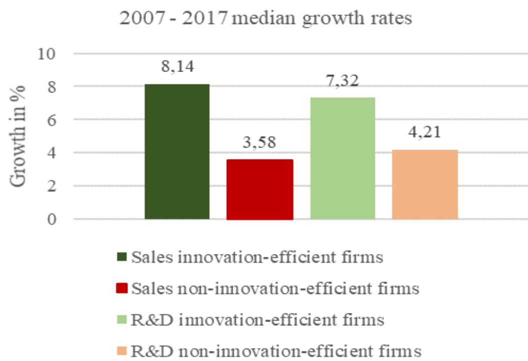

Figure 2. Median growth rates of non-/innovation-efficient firms of the period 2007-2017.

When ROIC was considered, non-innovation-efficient firms achieved an average annual ROIC of 10.82% and innovation-efficient firms 16.62% (see Figure 3). Similar results were drawn for the median annual EBITDA growth, innovation-efficient reached 10.23% annually compared to non-innovation efficient firms with 5.2%. In terms of valuation aspects innovation-efficient firms showed a higher EV/EBTIDA multiple with an annual average of 12.60% (median 9.58%) in comparison to non-efficient firms with 10.64% (median 7.21%). This means that the stock market tends to value innovation-efficient firms higher than inefficient ones. EV/EBITDA is an important measure in this study because it includes a market measure and can be seen as a leading indicator. Accounting measures are often characterised as lagging indicators (Bowen et al., 2010).

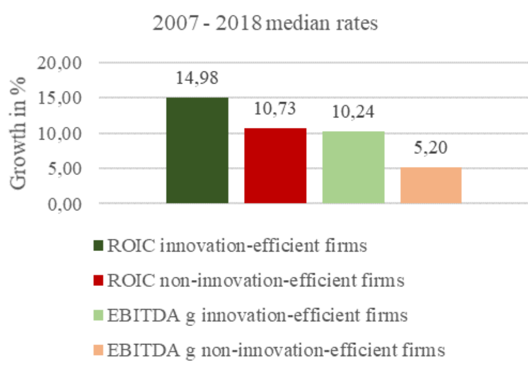

Figure 3. Median ROIC and EBITDA growth of non-/innovation-efficient firms of the period 2007-2017.

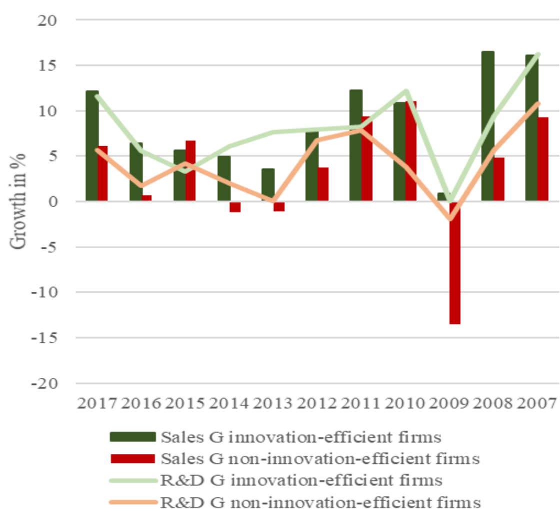

Figure 4. Median Sales and R&D expenditures growth of the selected firms over an 11 year period.

To assess the hypothesis, the four introduced linear regressions were analyzed. The independent variable was R&D expenditures growth and the explanatory variable sales growth. With the first linear regression, we tested the first part of the hypothesis (1a). With this linear regression (1a), we examined if the innovation-efficient firms showed a significant relationship between their sales growth and R&D expenditures growth during an economic upswing. Following we investigated if the innovation-efficient firms lower their R&D expenditures during an economic slowdown in relationship to their sales growth or not (2a). The same logic applied to the other two linear regressions for non-innovation-efficient firms. In conclusion, the aim was to show whether firms are adjusting their R&D expenditures to the current sales situation. The corresponding results are presented in Table 1. If the innovation-efficient firms were taken into account, it can be seen that sales growth was independent of R&D expenditure growth for these firms at an economic slowdown. For non-innovation-efficient firms, there was a relationship between sales growth and R&D expenditures growth both during an economic downturn and an upswing (see Table 1 1b & 2b). The linear dependency between R&D expenditures growth and sales growth was considerably (R^2 = .21) higher than for innovation-efficient firms (R^2 =0.1 / 0.0).

Test	Inter-section	standard errors (intersection)	beta coefficient	standard errors (beta)	Correlation R^2	p-Value	Pearson correlation
1a	9,99	2,20	0,55	0,06	0,10	0,00	0,32
1b	4,29	0,75	0,44	0,03	0,21	0,00	0,46
2a	27,33	9,23	0,60	0,49	0,00	0,22	0,07
2b	3,65	1,16	0,60	0,07	0,21	0,00	0,46

Table 1. Regression analyses to assess the hypothesis.

Regression analyses showed that innovation-efficient firms invested steadily into R&D expenditures growth and increased their R&D expenditures growth in comparison to their sales growth during an economic slowdown. In contrast, non-innovation-efficient firms invested more into R&D expenditures growth during economic upswings (positive sales growth) and declined their rates during slowdowns (negative sales growth). The corresponding growth rates for this data set are listed in Table 2. Innovation-efficient firms reported a median of 8.13% R&D expenditures growth over an economic upswing and 5.12% over a slowdown. In contrast, non-innovation-efficient firms showed a median of 5.77% R&D expenditures growth during the economic upswing and -0.25% during a slowdown.

	1a	1b	2a	2b
Sales Growth mean	14,51	11,86	3,25	-5,18
R&D expenditures Growth mean	17,56	7,44	29,11	0,56
Sales Growth median	9,49	6,16	3,57	-3,37
R&D Growth median	8,13	5,77	5,12	-0,25

Table 2. Mean and median growth rates during economic upswing and slowdown.

If the findings on regression analyses and the growth rates were considered, the hypothesis could not be rejected. However, it turns out that even innovation-efficient firms did not maintain the high R&D expenditures growth rates during an economic upswing.

V. CONCLUSION

Innovation-efficient firms showed superior performance in terms of valuation and financial indicators. Investing into innovation efficiency leads to a better future for firms: Innovation efficient firms stay ahead of their competitors due to their steady investment and realization of sales and earnings (EBITDA) growth.

In times of economic slowdowns, innovation-efficient firms kept investing into R&D expenditures. Non-innovation efficient firms cannot keep up with this pace set by the top performers.

Our results are in accordance with Hirshleifer et al. (2013) who also discovered that innovation-efficient firms perform better in operating future performance than non-efficient ones and are valued higher by the market. Innovation-efficient firms tend to be smaller in terms of their market capitalisation and can easily convert their innovation capabilities into firm value (Rubera and Kirca, 2012); this characteristic was also found in our data set.

A limitation regarding the data composition must be mentioned. In order to prove the hypothesis, the firms were divided into innovation-efficient and non-innovation-efficient firms. It did not matter whether a firm was only once or every year among the top 30 or bottom 30 firms in terms of innovation efficiency in the period considered. In order to investigate the impact on the results, we performed the linear regression analysis again. On an annual basis, we selected the top 30 and bottom 30 firms as innovation-efficient and non-innovation-efficient respectively. The findings were the same; during an economic slowdown, the non-innovation-efficient firms invested significantly less in R&D expenditures, reflecting their decline in sales. However, innovation-efficient firms kept their R&D expenditures high or even increased them.
In future studies it might be interesting to investigate how patent activities change during the economic ups and downs of innovation-efficient or non-innovation-efficient firms.

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