BETTER OFF WITHOUT YOU?

A STUDY ON CAPITAL ALLOCATION EFFICIENCY OF SPIN-OFFS IN THE UNITED STATES

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Abstract:

Through this paper we examine the internal capital allocation efficiency of spun-off entities, before and after completing spin-offs from their respective parent companies. The study involves a collection of 78 public, corporate spin-offs in the US during the time period 2005-2016. Although indicating that the firms' sensitivity to investment opportunities, measured by industry median Tobin's Q, increases, we find no significant evidence in our thesis supporting that spun-off entities from diversified firms improve their capital allocation efficiency post spin-offs. However, statistically significant evidence is obtained specifically supporting that large spun-off entities and single-segment spun-off entities operating in industries experiencing a low volatility in industry median Q, indeed improve their capital allocation efficiency post spin-offs. Conclusively, our findings indicate that the undertaking of spin-offs may have a positive effect on the internal capital allocation of the spun-off entities, being larger for entities with specific characteristics.

Keywords:

Spin-offs, Capital Allocation Efficiency, Investments, Tobin's Q

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1. Introduction

A spin-off is a type of divestiture where the parent company distributes new shares of an existing division or business, pro rata to its existing shareholders, and creates a new independent company. Studies on spin-offs' effect on shareholder wealth have concluded a positive relationship and driven a trend of an increased amount of spin-offs within the corporate world during recent years. The shareholder wealth from a spin-off is generated through an increased market valuation, that stems from expectations of value creation (Miles and Rosenfeld 1983). Less research has been conducted regarding the internal implications of spin-offs. Comment and Jarrell (1995) provide evidence that greater corporate focus results in increased efficiency and shareholder wealth, which also is a common motive for conducting spin-offs. Similar to Gertner, Powers and Scharfsten (2002) we aim to investigate the effects on internal capital allocation and investment efficiency for spun-off entities after conducting a spin-off from its parent company.

Subsequently, this thesis undertakes to address the following main question: *Do spun-off entities from diversified firms improve capital allocation efficiency post spin-off?* Similar to Gertner et al. (2002) and Ahn and Denis (2004) this study is conducted for listed companies in the US, but for a more recent time period, 2005-2016. This specific time period is interesting due to the lack of recent research and the observed increase in spin-offs during the period. In addition to the aforementioned baseline question, other contingencies are tested that previously have been left unaddressed: *Do larger spun-off entities and single-segment spun-off entities operating in industries with a low volatility in investment opportunities, improve their capital allocation efficiency relatively more post spin-off?* It is interesting to investigate if the size of the spin-off and the volatility of the industry's investment opportunities have an effect on the internal capital allocation, since this can provide guidance for management whether a spin-off would be beneficial for the specific entity and the parent company's shareholders.

Central to studies conducted by Ahn and Denis (2004), Gertner et al. (2002) among others is Tobin's Q. Tobin's Q ratio is calculated through dividing the market value of a firm's capital stock by its replacement value. Consequently, in this thesis Tobin's Q is used as a proxy for investment opportunities, basing the lack of investment efficiency on a suboptimal allocation of investments in high and low Q businesses. In order to gain insight in how a spin-off affects the spun off entity's allocation of internal capital, the sensitivity of investment to Q is observed.

To investigate the aforementioned research questions, fixed effect panel data regressions are constructed. Time fixed effects are used to control for changes in investment ratio over time and macroeconomic shocks. The investment ratio of a spun-off entity represents the dependent variable and is defined as capital expenditures normalized by assets. The interaction term consists of the independent variable *Industry Median q* measuring the investment opportunities in the industry, and the dummy variable *pre* indicating the years before and after the spin-off. This term is expected to have a negative and significant alignment with the dependent variable investment ratio. Consequently, it would indicate that the sensitivity to Q increases within spun-off entities after spin-offs are conducted, which would provide supporting evidence that spin-offs allocate their internal capital more efficiently as independent units, rather than part of their parent companies. Further, we investigate if the spun-off entities' differences in size and experienced volatility of industry median Q have an effect on their internal capital allocation by separating the firms into different groups.

In this thesis, we find no significant evidence supporting that spun-off entities from diversified firms improve their capital allocation and investment efficiency post spin-offs. The value signs of the coefficients in the model are although in line with Gertner et al. (2002), indicating that the sensitivity to Q increases for post spin-off periods relative to pre spin-off periods. However, due to statistical insignificance this indiciation should be interpreted carefully. The relatively small sample size and use of industry median Q as a proxy for investment opportunities are potential reasons for loss of statistical significance.

For the second hypothesis we find significant results supporting that larger spun-off entities allocate their capital more efficiently post spin-offs. On the other hand, we find that the sensitivity to Q for smaller spun-off entities increases *before* spin-offs. These results are, however, not significant and should therefore be interpreted with caution.

Regarding the third hypothesis we find significant results supporting that single-segment spin-offs operating in industries experiencing a low volatility in industry median Q allocate their capital more efficiently post-spin-offs. This is in line with our predictions and of potential interest to companies in the spin-off decision making process.

The thesis is structured in the following way: Section two starts off with an overview of theories and concepts, followed by a literature review of the most important research findings within the area. Section three presents the empirical background consisting of the data collection process, our hypotheses and methodology. Tests of the model assumptions are also included to assess the robustness of the regression model. Section four further builds on the data and presents the results as well as analysis of the conducted regressions. This is followed by a discussion of the findings and limitations of our research. Lastly, section six concludes our findings briefly and presents proposed directions for future research.

2. Theoretical Framework and Literature Review

2.1 Theoretical Framework

Diversification/Conglomerate Discount

The Diversification Discount is a financial concept describing how the stock market values a diversified firm less than the sum of the different parts and assets it consists of. A diversified firm is defined as a firm that operates or owns a number of unrelated business segments or firms (Maksimovic, Phillips 2002 and Laeven, Levine 2007). Rajan, Servaes and Zingales (2000) provide evidence supporting the diversification discount and find that diversified firms incur lower benefits and higher costs compared to more focused firms. Burch and Nada (2003) argue that this discount partly occurs due to the increased difficulty of effectively managing an array of different segments and divisions, compared to only operating a single-segment or more focused firm. The aforementioned researchers further study this area in connection to spin-offs, where a conclusion is drawn indicating that the diversification discount is an explanatory factor in the loss of value for a diversified firm. Furthermore, Laeven and Levine (2007) provide evidence that large diversified firms incur additional agency costs and internal conflicts, resulting in a situation where the costs of diversification exceeds the related benefits.

Tobin’s Q

The Tobin’s Q concept was created in 1961 by James Tobin. The Q ratio is calculated by dividing the market value of a company by the replacement value of its assets. In financial research, Tobin’s Q has previously been used with a variety of purposes, such as explaining the relationship between investments, the capital stock and diversification (Jose, Nichols, Stevens 1986) as well as examining the effect of ownership structure on firm value (Cho 1998). Should a firm’s Tobin’s Q ratio equal one, the market value precisely reflects the recorded assets of the company. Should the ratio exceed one, the market value is consequently higher than the recorded assets, implying that the firm holds value that is not measured in the assets. Tobin’s Q can further be related to investments. A Q larger than one implies that the firm has greater prospects to make capital investments, and the opposite if Q subceeds one. Scharfstein (1988) found that multi-segment firms have lower Q ratios than single-segment firms, and that they also tend to invest more in low-Q industries compared to high-Q industries.

Gertner et. al (2002) and Ahn and Denis (2004) use a proxy for Q when studying this particular area. The calculation of the proxy is calculated through dividing the market value by the book value, instead of the replacement value, since it is difficult to measure the actual replacement value of assets. This proxy is considered to have no significant effect on the results (Perfect and Wiles, 1994) and is therefore applied in our thesis as well.

2.2 Literature Review

Internal Capital Markets and Inefficient Investment Allocation

The internal capital market is an important mechanism managing decisions with regards to capital allocation and investment efficiency. This includes internal corporate questions such as how a diversified firm should distribute its capital between different business units in order to exploit the best possible investment opportunities? (Scharfstein, 1998).

Scharfstein (1998), Shin and Stulz (1998) and others, have studied the efficiency and functionality of internal capital markets by studying the correlation between firms' capital expenditures and the investments opportunities that exist in the industries where they operate, usually measured by the industry median Tobin's Q. The industry median Q is in the aforementioned research defined as the median Q for all companies operating in the same industry, which is usually defined as companies possessing identical three-digit SIC codes. The Standard Industrial Classification (SIC) is a system for classifying industries by specific four-digit codes. See Appendix 1 for further guidance.

Scharfstein (1998) found that conglomerate firms tend to invest more in low Q-divisions, and less in high Q-divisions, compared to more focused firms. Research by Rajan et al. (2000) further supports Scharfstein's argument by finding that conglomerates invest more in industries carrying poor investment opportunities. Additionally, this is supported by Shin and Stulz (1998) who found that there is no systematic way in how firms allocate the capital to divisions experiencing superior investment opportunities. The aforementioned arguments provide support for potential inefficiency problems related to internal capital allocation within diversified firms.

Rajan et al. (2000) further conclude that an increased diversity in opportunities and resources between different divisions decrease investment efficiency, compared to more homogenous divisions. This can partially explain the diversification discount, reflecting how the stock market tends to value diversified firms lower than its more focused peers. Further, it indicates a positive correlation between the firm's size and its experienced diversification discount.

Spin-Offs: Motivation and Value Creation

A spin-off is, as previously mentioned, a type of divestiture where the parent company distributes new shares of an existing division or business, pro rata to its existing shareholders, creating a new independent company. The diversification discount can drive diversified firms to conduct spin-offs in order to increase firm value and reach a more focused operational structure. Miles, Rosenfeld (1983) and Daley, Mehrotra and Sivakumar (1997) among others present data proving that both parent companies and the spun-off entities experience cumulative positive abnormal excess returns at the announcement of spin-offs, as well as in the long-run. Miles and Rosenfeld's (1983) findings show that the increased shareholder wealth is more substantial for larger spin-offs, compared to its smaller peers. Daley et al. (1997) further conclude that spin-offs create excessive value when unrelated businesses are divested, since it allows managers to focus on the company's core operations.

Spin-offs: Investment Allocation Efficiency

Gertner et. al (2002) examine the spun-off entities' sensitivity to Q pre and post spin-off, to evaluate the changes in their investment allocation efficiency. The sensitivity term represents the firms' ability to detect changes in Q, resembling investment opportunities, and adapt the corporate investments accordingly. Thus, a spin-off experiencing an increase in its relevant industry median Q, i.e. investment opportunities, and that subsequently increases its investments can consequently be regarded as more sensitive to Q, compared to an identical firm holding its investments flat, although experiencing an equal increase in investment opportunities.

Gertner et. al, (2002) found that spun-off entities improve their internal capital allocation efficiency post spin-offs. They also saw an overall increased sensitivity of investment to Q after the spin-off, with the results being most observable for spin-offs operating in unrelated industries to their parents, as well as when there is a positive reaction to the spin-off announcement. These findings are further supported by Ahn and Denis (2004) who provide evidence that spin-offs will reduce the discount of diversified companies and improve the allocation of capital expenditures across divisions, which creates excess value. Ahn and Denis (2004) and Gertner et. al (2002) studied this topic from different perspectives, but collectively concluded that spin-offs may lead to an improved capital allocation efficiency both for parents and spun-off entities.

Spin-offs: Industry-specific Investment Opportunities and Volatility

As stated previously, Gertner et. al (2002) find an overall increased sensitivity of investment to Q after the spin-off, where the results are most observable for spin-offs that operate in industries unrelated to those of their respective parents, indicating that industry-specific characteristics is an explainable factor when studying internal investment efficiency. However, defining a measure of relatedness is problematic and acted as a limitation to Gertner et. al's paper (2002). Kallapur and Trombley (2001) argue that industry-specific investment opportunity sets are primarily determined by factors such as barriers to entry, product life-cycles and competitive environment. Furthermore, they emphasize a huge variation in these factors between, and over time also within, different industries, as well as the effect they may have on firms' investments.

Since market valuations are the main drivers of changes in the industry median q ratios, and thus investment opportunities, the effect of stock market volatility on spun-off entities' internal investment efficiency ought to be examined. Zuliu Hu (1995) found that excessive volatility might weaken the stock market's role as a forecasting mechanism and cause firms to systematically ignore volatile short-run changes and instead opt for long-term investment decisions.

3. Empirical Background

3.1 Data

3.1.1 Data Collection - Spin-offs and Parent Companies

The first step in collecting the relevant data includes extracting a list covering all the spin-offs in the United States during the time period 2005-2016 from the SDC Platinum Merger and Acquisitions Database. SDC Platinum is a software application owned by Thomson Reuters and used as a database for analyzing spin-offs and other types of deal activity. From the aforementioned database we collect the name of the parent company, spun-off entity, the SIC-codes, the tickers, the size of the spin-off as well as the effective year of completion. The sample was restricted by only including parent companies with a public status and spin-offs with a transaction value greater than zero. These two restrictions are appropriate since we are only interested in public parents and spin-offs, and the transaction value is an important variable for our second research question. The restriction for transaction value removed 316 of 518 spin-offs, which left us with a sample of a total of 202 spin-offs. Afterwards, the sample was restricted manually by removing companies with SIC-codes between 6000-6799, including companies within the financial sector, such as banks and insurance companies, which are often highly levered and therefore inappropriate when using Tobin's Q. Furthermore, financial and non-financial companies are usually separated in accounting due to the different financial reporting methods implemented. This screening left us with a sample of 162 spin-offs.

The sample was further restricted and adjusted by only including tax-free spin-offs, as well as manually ensuring that the transaction actually was a spin-off. A spin-off is generally tax-free when the spun-off entity becomes a publicly owned, independent company with its own ticker symbol and management team. This can occur if the parent company distributes at least 80 % of its shares to existing shareholders on a pro rata basis or by issuing an exchange offer to current shareholders. Other requirements to classify a spin-off as tax-free is that the separating entity has been an active operation of the parent company for at least five years prior to the spin-off, and that this entity, as well as the parent company, is an active business immediately after the spin-off (Section 355, Internal Revenue Code). To ensure fulfillment of the aforementioned requirements, the sample has been manually restricted by reading relevant news articles and SEC filings. If a spin-off is classified as tax-free in an SEC filing, one can assume that the criterias are fulfilled. Furthermore, spin-offs and parent companies that have partaken in or experienced certain events that affect comparability, such as loss of independence directly after merger, tracking stock issues or consecutive bankruptcy, have been removed. These spin-offs are classified as “complex transactions” in our study. An example of a complex transaction is the spin-off of Motorola Inc, Motorola Mobility, which merged with Google immediately after the spin-off had occurred. After executing the aforementioned adjustments, we are left with a sample of 105 spin-offs.

The final step in adjusting the sample of spin-offs includes removal of parent companies without any firm level Compustat financial data available three years preceding and following the spin-off, as well as spun-off entities missing the equivalent data for at least one year preceding and following the spin-off completion. Compustat is a database including financial information, such as income statements and balance sheets, for more than 24,000 publicly held companies. Compustat is accessed through Wharton and extensively used globally, both within research and the corporate world. The variables obtained from this database are selected to contribute in testing our research questions. This includes identification variables, such as tickers, company names and SIC codes, as well as financial data, such as sales, total assets and market value of equity. After manually checking the relevant companies we are left with a final sample of 78 spin-offs between 2005-2016. The manual screening in accordance with set criterias is essential in order to extract a useful and comparable sample preventing the study from yielding misleading and incorrect results. Moreover, these criterias are very similar to those used by Gertner et al. (2002) and Ahn and Denis (2004).

Table 1 below presents the cleaning process for the spin-off sample and clearly states the number of spin-offs removed in each step, in accordance with set criterias. Removed companies are only included in one of the categories below, although some overlap might be present. For example, a company considered “Complex Transaction” due to a consecutive merger, could also classify as “No Data on Compustat”. Therefore, conducting the cleaning process in a different order would result in other amounts of spin-offs removed in each step, however, the total number of removals would end up identical regardless.

Table 1

Cleaning Process for Spin-off Sample

Table 1 presents the cleaning process of the SDC Platinum Data for public spin-offs during 2005-2016 in the US. The total number of spin-offs from the SDC Platinum Database after restrictions is presented followed by the number of spin-offs eliminated manually in accordance with set criterias.

Number of completed spin-offs from SDC Platinum Database:	**202**
Financial Companies (SIC-codes: 6000-6799)	-40
Complex Transactions	-43
Not Tax-free	-14
No Data on Compustat	-27
Final Sample:	**78**

In this sample, there are 78 Parents undertaking the 78 spin-offs. Should a parent have conducted more than one spin-off, each spin-off would be treated as a specific event. However, in our sample there is an equal amount of both. On the other hand, there is one entity that has both acted as a parent company and a spin-off during the time period. These events are separated by the variable "type" in the data set, which defines whether the company was a spun-off entity or a parent company during that specific event year. Thus, they are therefore treated as individual observations.

The yearly number of spin-offs fluctuates significantly during the observed years, with a majority of the spin-offs occurring at the end of the sample period. This supports our interest in conducting a replication of Gertner et. al's (2002) study for a more recent time period. The total transaction value also fluctuates substantially and is partly driven by the number of spin-offs, but also the difference in actual size of each specific spin-off. The number of conducted spin-offs is the greatest in 2015, being 15 and accumulating a total transaction value of 94,738 million US dollars. Table 2 presents the total number of spin-offs and the total transaction value each year.

Table 2

Number of Spin-offs and Total Transaction Value per Year

Table 2 presents the number of spin-offs and the total transaction value each year for our final sample. The year represents the effective fiscal year of the spin-off completion and the total transaction value is the market value of the spin-off on the first day of trading on the stock exchange.

Year	Number of Spin-offs	Total Transaction Value ($mil)
2005	2	173
2006	2	3 938
2007	6	77 621
2008	7	4 337
2009	3	38 007
2010	2	5 276
2011	6	23 678
2012	7	53 128
2013	5	60 867
2014	12	25 865
2015	15	94 738
2016	11	36 932
Total	78	424 559

For all the parent companies and spun-off entities in our final sample, firm level financial data is gathered from Compustat for the three years preceding and following the spin-offs. In some cases, due to consecutive mergers, bankruptcies or other reasons, financial data is not available for the entire relevant time period. The existing financial data is then used in the creation of all the relevant variables applied in the regressions.

3.1.2 Data collection of single-segment firms and weighting of spin-off segments

The final sample representing all the relevant spin-offs and their respective parent companies is now complete. The second step is to collect data for single-segment firms in order to calculate the Industry median Q for all the spin-offs in the sample. This variable is essential for the regressions, since it represents the experienced investment opportunities of the spun-off entities. The reason we calculate an industry median Q rather than a firm-specific measure is because the spin-offs are not publicly traded when part of their parents, which hinders us from obtaining all necessary data for the variable. It would be possible to use a firm-specific Q for the period following the spin-off completion, but similar to Gertner et.al (2002) we use the industry median Q for both periods to avoid differences between the two. Both Gertner et al. (2002) and Ahn and Denis (2004) provide evidence that their results are robust for other measures of industry median Q as well.

Since spun-off entities themselves might operate in several industries before or after the spin-off occurs, we also include these segments' four digit SIC-codes and calculate a weighted average of the various industries in which the spin-off operates. The weighting is based on the ratio of assets the firm reports in each four digit SIC-code segment. In order to conduct the weighting, segment data is downloaded from Compustat for all the spun-off entities. For example, the spun-off entity Avanos Medical is divided into two segments, "Medical Devices" and "Surgical & Infection Prevention", with the four digit SIC-codes 3845 and 3842, respectively. For 2016, the year after its spin-off was completed, 47% of the company's assets was reported in Medical Devices, whilst 53% was reported in Surgical & Infection Prevention. Thus, Avanos Medical's Q for 2016 will equal 0.47*3845 industry median Q 2016 + 0.53*3842 industry median Q 2016. The industry median Q for the four digit SIC-codes 3845 and 3842 was 4.69 and 2.49 respectively. Consequently, the Q for Avanos Medical in 2016 was 3.52 (0.47*4.69 + 0.53*2.49 = 3.52). The weighting process is a replicated process from Gertner et al. (2002) and crucial to the study by yielding a reasonable estimation of the spin-offs' investment opportunities.

For the majority of the spin-offs included in the sample, segment data prior to year -1 is unavailable. In those cases the segment weighting for year -2 and -3 are therefore conducted by adopting the same method as Gertner et al. (2002), which is using the segment weights from the earliest available year as proxies. However, even though weights in some cases are proxies, the industry median Q's are always from the correct years. Should the case instead be that the firm has turned single-segment after being spun-off, causing segment data to be unavailable in any of the years +1,+2 or +3, the primary SIC-code of the firm is used to identify the correct industry median Q to be used in calculation of the spin-off's Q ratio.

Table 3 shows the distribution of the maximum number of segments i.e. industries each spun-off entity operates in during the three years preceding and following the spin-off, as well as the effective year of completion. 55 spun-off entities are single-segment firms and 23 are multi-segment firms.

Table 3

Spin-offs' Maximum Distribution of Segments

Table 3 presents the distribution of the maximum number of segments i.e. different industries based on SIC-codes that the spin-offs in the sample operate in. 55 spin-offs operate in only one industry, 15 in maximum two industries, 5 in maximum three industries, 2 in maximum four industries and 1 in maximum five industries.

Spin-offs included in sample	**78**
Single-segment firms	55
Two-segment firms	16
Three-segment firms	4
Four-segment firms	2
Five-segment firms	1

To construct the final sample including all the spun-off entities' SIC codes and operating segments, we extract segment data from Compustat for all 2-digit SIC-codes. The data for 2-digit SIC codes naturally also includes all available 3-digit and 4-digit SIC codes. All parent companies and spun-off entities are excluded. Further, since we only use single-segment firms in the industry median Q calculation, all multi-segment firms are removed. Similar to Gertner et al. (2002), the definition of single-segment is a firm that reports all of its sales in a certain SIC code.

After constructing the aforementioned dataset consisting of single-segment firms operating in the spin-offs' industries, firm level annual financial data based on tickers is gathered from Compustat. Variables necessary to calculate Q are also downloaded. Q is calculated as (Book value of assets + market value of common equity - book value of equity - deferred taxes) / Total Assets. This proxy of Q is used by Gertner et. al (2002) among others and therefore considered an appropriate definition. Since Q is essential in the analysis, companies that display missing data for Q are removed. Using this sample, industry median Q is calculated for all the spun-off entities in our sample. Similar to Gertner et. al (2002) we require at least five firms to calculate the industry median Q. Thus, we start by screening 4-digit SIC-codes and consequently move down one digit at a time, to 1-digit SIC codes if necessary, until five applicable firms are attained. Finally, we have obtained the industry median Q's for the spun-off entities in our sample and merge this data with all other relevant financial data.

In order to obtain sufficient data to test our third hypothesis, we calculate the volatility, proxied by the standard deviation, of the industry median Q for all the industries i.e. SIC codes that the spin-offs operate in. This is further constructed as a variable taking on the value of 1 for spin-offs operating in industries with a high volatility in industry median Q, and the value of 0 for spin-offs operating in industries with a low volatility in industry median Q. For our sample, we could conclude that the predominantly high volatility industries were manufacturing and services, whilst the low volatility industries consisted of transportation, communication, electricity, gas and sanitary service as well as wholesale trade.

3.1.4 Summary Statistics

Table 4 provides summary statistics for the parents and spun-off entities in years -1, 0 and +1. The variables for the two panels are defined in accordance with Gertner et al (2002). Investment ratio is defined as capital expenditures divided by total assets and Operating profit ratio is defined as operating income before depreciation and amortization divided by total assets. Industry median Q represents the median Tobin's Q for the industries in which the spin-offs operate. In order to avoid problems with the data and risk drawing misleading conclusions, missing variables for Investment ratio and Operating profit ratio are dropped. This results in a drop of 37 missing observations, which ought to be considered acceptable since it equals less than 5 % of the total number of observations. Furthermore, the dependent variable investment ratio is winsorized at the 1st and 99th percentile to avoid outliers causing biased regressions.

The variables included in table 4 are total assets, sales, investment ratio, operating profit ratio and industry median Q. Regarding interpretation of the table statistics, the median can generally be considered a more appropriate measure for the variables, since the mean includes outliers that have significant effects on the descriptive statistics. In panel I and II in Table 4 it is shown that the median, of both total assets and sales for all included years, for parent companies are around two and a half to four and a half times the size of the corresponding medians for the spin-offs. Thus, one can conclude that the parent companies are of much larger size than the spun-off entities. Table 4 further displays a close similarity in median investment ratio of parents and spin-offs, as well as in operating profit ratio. Even though the median is the most suitable measure, it should however be noted that the mean operating profit ratio of spin-offs is lower than the parents' during all years, indicating that undertaking spin-offs might be a strategy for parent companies to dispose of less profitable divisions or divisions in need of additional funding.

Lastly, panel I in Table 4 also includes industry median Q ratios for the spin-offs, which represents the investment opportunities that exist in the industries where the spin-offs operate. The table allows us to conclude that the median of the industry median Q is higher before the spin-off completions, and lower thereafter. Furthermore, both the median and mean exceeds 1 for all periods, indicating that the companies theoretically possess greater prospects to make capital investments compared to firms operating in industries with a Q below 1.

Table 4

Summary Statistics for Spun-off Entities and Parents in Years -1, 0 and +1.

Table 4 shows descriptive statistics for parents and spun-off entities in years -1, 0 and +1. Year -1 represents the last full fiscal year preceding the spin-off and year +1 represents the first full fiscal year following the spin-off. Year 0 represents the fiscal year when the spin-off is completed. Panel I provides summary statistics on the sample of spun-off entities and Panel II provides summary statistics on the sample of parents.

Panel I: Summary Statistics Spun-off Entities	*Year -1*	*Year 0*	*Year 1*
Total Assets (Million $)			
Mean	6 171	6 864	6 866
Median	1 606	1 706	1 700
Standard Deviation	12 547	14 502	14 325
Observations	78	78	78
Sales (Million $)			
Mean	6 995	6 985	6 974
Median	1 561	1 643	1 571
Standard Deviation	22 456	21 383	20 786
Observations	78	78	78
Investment Ratio			
Mean	0,063	0,051	0,049
Median	0,035	0,033	0,032
Standard Deviation	0,066	0,049	0,046
Observations	78	78	78
Operating Profit Ratio			
Mean	-0,054	0,117	0,090
Median	0,128	0,122	0,116
Standard Deviation	1,743	0,137	0,224
Observations	78	78	78
Industry Median Q			
Mean	2,039	1,958	2,040
Median	1,878	1,749	1,752
Standard Deviation	0,730	0,722	0,828
Observations	78	78	78

Panel II: Summary Statistics Parent Companies	*Year -1*	*Year 0*	*Year 1*
Total Assets (Million $)			
Mean	19 932	15 382	13 609
Median	7 223	4 886	4 344
Standard Deviation	30 048	23 109	19 876
Observations	78	78	78
Sales (Million $)			
Mean	17 777	12 159	10 567
Median	5 632	4 221	4 034
Standard Deviation	34 872	23 129	20 003
Observations	78	78	78
Investment Ratio			
Mean	0,053	0,051	0,053
Median	0,033	0,037	0,032
Standard Deviation	0,053	0,049	0,060
Observations	78	78	78
Operating Profit Ratio			
Mean	0,120	0,138	0,130
Median	0,119	0,114	0,117
Standard Deviation	0,049	0,156	0,113
Observations	78	78	78

3.2 Methodology

3.2.1 Hypotheses

The hypotheses have been formulated based on previous research within the area, which is further described in the Literature Review section, including our area of interest.

Hypothesis 1: Spun-off entities from diversified firms improve capital allocation efficiency post spin-off. This hypothesis is supported by research from Gertner et al (2002), Ahn and Denis (2004) among others. It implies that we expect that the spun-off entities' investments are less sensitive to Q when part of diversified firms, compared to when they are operating as independent entities. Consequently, the hypothesis implies that the capital allocation efficiency will improve for spun-off entities after the spin-off from their respective parent companies are completed.

Hypothesis 2: Larger spun-off entities improve their capital allocation efficiency relatively more post spin-off. This hypothesis is partly supported by research conducted by Miles and Rosenfeld (1983) and Daley et. al (1997) among others, which have concluded that the increase in shareholder wealth is more substantial for larger spin-offs, compared to smaller ones. Furthermore, allocating capital efficiently is said to naturally become more difficult when companies grow in size and diversify (Comment and Jarrell 1995). Several segments and investment opportunities then emerge within the corporation, who all require a part of the limited cash balance and managerial focus of the parent company. The internal capital market mechanism in many large companies, where capital allocation decisions are taken on a higher corporate level further away from each specific investment opportunity, logically creates challenges in efficiently allocating the internal capital. For example, a large spin-off requiring a significant amount of capital expenditures might be overlooked when being part of a corporation required to allocate capital to several other large segments, or possibly a multitude of smaller segments. Consequently, we believe that larger spun-off entities will improve their capital allocation more efficiently compared to their smaller peers.

Hypothesis 3: Single-segment spun-off entities operating in industries experiencing low volatility in industry median Q improve their capital allocation efficiency relatively more post spin-off. The association between stock market volatility, consequently causing volatility in industry median Q, and corporate capital investments has been thoroughly documented by Fama (1990) and Cochrane (1991), amongst others. Furthermore, Hu (1995) found that excessive volatility might weaken the stock market's role as a forecasting mechanism and cause firms to systematically ignore volatile short-run changes and instead opt for long-term investment decisions. Additionally, we find it logical that firms experiencing volatile changes in investment opportunities might have a more difficult time grasping and efficiently acting on them. The aforementioned findings intrigues an examination of which effects the volatility in investment opportunities has on the spun-off entities' capital allocation efficiency after becoming independent and advancing the decision making to management closer to the firms' operative industries. This question forms the basis of our third hypothesis testing if single-segment spun-off entities operating in industries experiencing low volatility in industry median Q will improve their capital allocation efficiency relatively more post spin-off. Due to difficulties in correctly estimating the volatility in industry median Q for multiple-segment firms, only single-segment firms are included in the hypothesis sample.

3.2.2 Fixed Effect Regression Model

To empirically investigate our hypotheses, we will use panel data. Panel data is necessary since we possess observations for the sample companies over repeated time periods. All observations are constructed in a seven-year panel for each specific spin-off, representing the three years preceding the spin-off, the fiscal year when the spin-off is completed as well as the three years following the spin-off. The dataset is unbalanced due to the fact that we do not have full time period data for all spin-offs. This is because some spun-off entities do not report any financial data, are consecutively merged, acquired or bankrupt, or for other reasons do not display complete financial data for all relevant years. Worth noting, this does not necessarily have an effect on the regressions conducted. Using panel data, we run fixed effect regressions similar to Gertner et al. (2002).

3.2.3 Variables

To determine whether spin-offs affect investment behavior, we study changes in the sensitivity of investment to Q, for the spun-off entities before and after spin-off completion. The dependent variable, *Investment Ratio* (Capital Expenditures/Total Assets), will therefore represent investments. Capital Expenditures can be seen as the measure of investment, which then is normalized by assets. There are other possible measures that could be used to measure investments, and the potential implications of the chosen definition will be examined in the discussion section.

The key independent variable is *Industry Median Q*, which is calculated as the median Tobin's Q for all single-segment firms operating in the same industries as the spun-off entities. This variable is used to measure the investment opportunities available to the specific spun-off entity during the period before and after spin-off completion.

The second key independent variable is *Pre*, which is a dummy variable taking on the value of 1 for the three years preceding the spin-off and the value 0 for the three years following the spin-off. The fiscal year when the spin-off occurs is not included in the regressions. This variable is important in order to draw conclusions about changes in capital allocation decisions after a spin-off is completed.

The third independent variable is the interaction term *Industry Median Q * Pre*, which is the product of the two aforementioned variables. Consequently, the variable is interesting to include in the model to enable an examination of the relationship between the two previous variables, and further also their relationship with the investment ratio.

Further, it is essential to include control variables that are expected to affect the investment ratio. The firm-specific control variables included are *Operating profit ratio*, in accordance with Gertner et. al (2002), and *Net Income*. The operating profit ratio is defined as operating income before depreciation and amortization divided by assets. It represents the annual cash flows of the spun-off entities available to capital expenditures, which naturally ought to affect the level of investments. The variable is constructed as a continuous variable. The second firm-specific control variable is net income. It is important to control for since a negative net income might entail financial problems. If a company has a negative net income or is in financial distress it is highly likely that its investment ratio will be affected. Net income is constructed as a dummy variable, taking on the value of 1 if succeeding zero and the value of 0 if exceeding zero.

Furthermore, we include *fiscal year dummy variables* to control for fiscal year fixed effects. Year dummy variables are included for 2003-2019, where Dummy 2003 equals 1 when the effective date is 2003 and 0 otherwise, and so on for all the years included in the sample. The dummy variables should account for changes in investment ratio over time and macroeconomic happenings. The regressions also include *Firm fixed effects*, which is included in the intercept of the model. Firm fixed effects are used to control for firm characteristics that are unobserved and can cause biases.

3.2.4 Estimated Regression Models

Hypothesis 1

For our first hypothesis and baseline question the regression examines whether there is a change in the sensitivity of investment to Q, reflecting a potential change in the investment behavior of a spun-off entity after completing a spin-off from its parent company. The regression includes the control variables operating profit and net income, as well as time dummies and firm fixed effects.

Equation 1

$$Investrat = \beta_{0i} + \beta_1 IndMedianQ_{it} + \beta_2 Pre_{it} + \beta_3 IndMedianQ_{it} * Pre_{it} + \beta_4 opprofit_{it} + \beta_5 NetInc + Fixed\,Year\,Effects + \varepsilon_{it}$$

With the regression above, our main focus variable is the interaction term *IndMedianQ*Pre*. For hypothesis one to be supported, the coefficient for this variable should be negative and statistically significant, which would imply an improvement in the capital allocation efficiency of spun-off entities in the post spin-off period relative to the pre spin-off period.

Hypothesis 2

The interesting addition relevant to hypothesis two is the size of the spin-offs. As argued before it is likely that the size of the spin-off affects the change in capital allocation efficiency. Equation 1 will be used to test this hypothesis as well, however the groups consisting of small and large spin-offs will be regressed separately. Large spin-offs are defined as those with a transaction value above the median and small spin-offs are defined as those with a transaction value below the median.

For this regression, we expect that the coefficient for the focus interaction variable *IndMedianQ*pre* will be negative and statistically significant for large spin-offs. Thus, the coefficient is therefore expected to be lower for small spun-off entities.

Hypothesis 3

For the third hypothesis we only include the 55 single-segment spin-offs from our main sample. As discussed earlier, the reason for this is the difficulty in estimating the volatility in industry median Q for multi-segment firms.

Equation 1 will be used to test this hypothesis as well, however the groups consisting of spin-offs operating in industries experiencing a high and low volatility in industry median Q respectively will be regressed separately. Spin-offs operating in industries experiencing an industry median Q volatility below the median are defined as low volatility Q, and the opposite for high volatility Q.

For this regression, we expect that the coefficient of the interaction term *IndMedianQ*pre* will be negative, statistically significant and larger in absolute size for spun-off entities operating in industries experiencing a low volatility in industry median Q.

3.2.5 Test of Model Assumptions

It is important to control for common problems arising when conducting fixed effect panel regressions in order to ensure robust regression results and thus correct conclusions. Robustness checks are conducted for the assumptions regarding no autocorrelation, homoscedasticity in error terms and no multicollinearity in the independent variables. A significance level of 5 % has been chosen for all the tests.

Homoscedasticity

An important assumption is that the regression model should experience homoscedasticity, which occurs when a group of random variables have a mean of 0 and are constant along the line of fitted values. Consequently, heteroscedasticity occurs if these requirements are not met. Heteroscedasticity can be highly problematic since it can negatively impact the validity of the regression model and produce distorted P-values (Carlson, Newbold, Thorn, 2013). In order to test for heteroscedasticity, we conduct Breush-Pagan tests for each regression. The test results imply the presence of heteroscedasticity in our error terms. To correct for heteroscedasticity, we run robust standard error regressions clustered by spin-off firms.

Autocorrelation

The second assumption tested is the absence of autocorrelation. A regression model should not contain autocorrelation, which means that the error terms are correlated over time. Consequently, autocorrelation can cause standard errors to be measured incorrectly and not experience constant variance. Since autocorrelation is more common when using panel data, it is essential to test for in our model (Carlson et. al 2013). To test for autocorrelation, a Wooldridge test is conducted. The test implies that there is no autocorrelation in our error terms. Since we use robust standard errors clustered by spin-off firms, potential autocorrelation would have been accounted for in the regressions.

Multicollinearity

Multicollinearity occurs when two or more independent variables are correlated. This does not necessarily imply that the model is wrong but makes it more difficult to distinguish the contribution of certain independent variables (Carlson et. al 2013). Since we introduce an interaction term in our model, the relevant input variables have to be centered to mitigate multicollinearity. In this case only *Industry Median Q* is centered, since it is a continuous variable. It makes no sense to center the dummy variable *pre*. In order to test for multicollinearity, it is appropriate to calculate the variance inflation factors (VIF). The results from these calculations are shown in Appendix 2. Historically, there has been a debate regarding which maximum level of VIF that is considered appropriate. According to Kennedy (2008), the maximum acceptable level of VIF is 10. Therefore, we can conclude that there is no serious concern regarding multicollinearity in our model.

4. Empirical Findings

4.1 Change of capital allocation for spun-off entities after spin-off

This part presents the regression results from the regression concerning hypothesis one and discusses the assumptions with regards to the coefficients.

$$Investrat = \beta_{0i} + \beta_1 IndMedianQ_{it} + \beta_2 Pre_{it} + \beta_3 IndMedianQ_{it} * Pre_{it} + \beta_4 opprofit_{it} + \beta_5 NetInc + Fixed\,Year\,Effects + \varepsilon_{it}$$

The results are presented in table 5 below.

Table 5

Regression results Hypothesis 1

Table 5 presents the regression results for Hypothesis 1.

	Full sample
Pre	0.00518
	(0.00721)
Industry Median Q	0.000372
	(0.00607)
*Industry Median Q * Pre*	-0.00527
	(0.00634)
Operating Profit Ratio	-0.0152***
	(0.000627)
Net Income	-0.0115*
	(0.00668)
Number of Observations	381
Number of Firms	78
R^2	0.313
Adjusted R^2	0.272
Firm Fixed Effects	Yes
Year Fixed Effects	Yes

Robust standard errors in parentheses
* $p < .10$, ** $p < .05$, *** $p < .01$

The positive coefficient for industry median Q implies that the investment ratio increases when industry median q increases, further implying that firms invest more when experiencing superior investment opportunities. This result is consistent with Gertner et. al (2002). However, the coefficient is very small and not statistically significant, therefore it does not provide sufficient evidence to conclude that the effect in fact is positive nor negative.

The negative coefficient for the interaction term *Industry Median Q*Pre* implies that the sensitivity to Q increases for post spin-off periods relative to pre spin-off periods. This is also in accordance with research conducted by Gertner et al. (2002). However, this coefficient is also not statistically significant, thus creating uncertainty regarding whether it has a positive, negative or no effect.

The control variable operating profit ratio is statistically significant on the 1 % level and the negative coefficient implies that when the operating profit ratio increases by 10 percentage points, the investment ratio decreases by 0.152 percentage points. Naturally, this result can be considered interesting, since one could argue that increased cash flows should result in increased investments, which is what Gertner et al. (2002) found, and not vice versa.

The dummy variable Net income is statistically significant on the 10 % level, and the negative coefficient implies that companies with a net income loss executes a relatively lower investment ratio, which is in line with our predictions.

All time dummy variables have negative coefficients and are statistically significant at the 1 % level. The negative coefficients imply that the annual average investment ratios in the sample are lower than the investment ratio for the base year 2003. Interestingly, we can also identify an increase in the coefficients for these dummy variables after the financial crisis in 2008, indicating an increase in the investment ratio since that year.

Since none of the independent variables are statistically significant, we cannot find any evidence supporting our first hypothesis. The absence of significant variables might be derived from our relatively small sample size. Furthermore, we are studying a different time period compared to previous research conducted by Gertner et. al (2002), Ahn and Denis (2004) among others, which might affect the results. In addition, industry median Q could be considered an uncertain proxy for investment opportunities, which will be further conferred in the discussion section.

Divergent residuals are not deemed to be influential on the results since removal of these observations do not change the results substantially or prompt statistical significance for the main variables. Therefore, these observations are kept in the regressions. Furthermore, running regressions without firm fixed effects do not affect the results significantly and are therefore included in all regressions.

The adjusted R-squared for our model is 0.272, which means that it explains 27.2 % of the variability in the investment ratio. This adjusted R-squared is very similar to those in previous research conducted by Ahn and Denis (2004) and thus validates the model.

4.2 Small vs. large size of spin-offs

This part presents the regression results and discussions of the coefficients with regards to hypothesis two. Consequently, the spin-offs are separated into two groups based on if their respective transaction value is below or above the sample median. Furthermore, the same regression as for Hypothesis 1 is conducted, however each group is regressed separately. Table 6 below presents the regression results for these two groups.

Table 6

Regression results Hypothesis 2

Table 6 presents the regression results when dividing the spun-off entities into a large and small group based on the size of their transaction value.

	Large Spin-offs	Small Spin-offs
Pre	0.00142	-0.00549
	(0.00726)	(0.0121)
Industry Median Q	0.00295	-0.00922
	(0.00428)	(0.0135)
*Industry Median Q * Pre*	-0.0146**	0.0127
	(0.00667)	(0.0114)
Operating Profit Ratio	0.0580*	-0.0148***
	(0.0295)	(0.00108)
Net Income	-0.0193	-0.00551
	(0.0116)	(0.00825)
Number of Observations	193	188
Number of Firms	39	39
R^2	0.338	0.404
Adjusted R^2	0.261	0.329
Firm Fixed Effects	Yes	Yes
Year Fixed Effects	Yes	Yes

Robust standard errors in parentheses
* $p < .10$, ** $p < .05$, *** $p < .01$

The positive coefficient for industry median Q for the large spin-offs implies a corresponding increase in investment ratio when industry median q increases, further implying that large spin-offs invest relatively more when experiencing superior investment opportunities. This is consistent with the coefficient for the overall sample. However, for small spin-offs the coefficient for industry median Q is negative, implying a negative relationship between investment ratio and investment opportunities. Neither group’s coefficient is statistically significant and should therefore be interpreted carefully.

The interaction term for large spin-offs is positive and statistically significant at the 5 % significance level. These results imply a statistically significant increase in sensitivity to Q for larger sized spun-off entities after spin-off completion, relative to the prior period as part of a diversified parent company. Furthermore, it indicates a possible improvement in the capital allocation efficiency of large spun-off entities post spin-off.

The aforementioned conclusion is not applicable to smaller spin-offs, for which our findings instead entail an insensitivity to Q after spin-off completion and rather higher sensitivity to Q *before* the spin-off occurs. These results are similar to those attained by Gertner et. al (2002), who found that spun-off entities operating in industries that are unrelated to their parents are more sensitive to Q before the spin-off. Yet they are unable to provide any sufficient explanation for this, which calls for a further investigation of these two phenomena in future research. However, this coefficient is not statistically significant and should therefore be interpreted with caution.

The operating profit ratio is statistically significant for both larger and smaller spin-offs. For large spin-offs the coefficient is positive and statistically significant on the 10 % level, which implies that an increase in operating profit ratio of 10 percentage points results in an increase in the investment ratio of 0.58 percentage points. This is in line with our predictions and research conducted by Gertner et. al (2002). However, for small spin-offs the coefficient is negative and statistically significant at the 1% level, implying that an increase in operating profit ratio of 10 percentage points results in a decrease in the investment ratio of 0.148 percentage points. Consequently, the aforementioned results are in line with the results for the first hypothesis.

The second control variable net income is not statistically significant for any of the groups. However, the signs on the coefficients imply that spin-offs with a net income loss executes a lower investment ratio, which is in line with the results for the overall sample.

The adjusted R-squared for the large spin-offs is 0.261, which means that the model explains 26.1% of the variability in the investment ratio. For the small spin-offs, the adjusted R-squared amounts to 0.329. Conclusively, the adjusted R-squared is very similar for the two regressions and also in line with the adjusted R-squared for the first hypothesis, which covers the full sample. Thus, the model can be considered valid.

4.3 Volatility in industry median Q

This part presents the regressions results and discussions of the coefficients with regards to hypothesis three. Consequently, the single-segment spin-offs are separated into two groups based on whether they operate in industries experiencing a high or low volatility in industry median Q. The same regression as for Hypothesis 1 is conducted, however each group is regressed separately. Table 7 below presents the regression results for these two groups.

Table 7

Regression results Hypothesis 3

Table 7 presents the regression results when dividing the single-segment spun-off entities into spin-offs operating in industries experiencing a high or low volatility in industry median Q.

	Low Volatility Q	High Volatility Q
Pre	-0.0171	0.00306
	(0.0160)	(0.0165)
Industry Median Q	0.0280	-0.0174
	(0.0300)	(0.0146)
*Industry Median Q * Pre*	-0.0540**	-0.00243
	(0.0244)	(0.0170)
Operating Profit Ratio	0.0875**	-0.0155***
	(0.0405)	(0.000818)
Net Income	-0.00527	-0.0167
	(0.0101)	(0.0214)
Number of Observations	134	125
Number of Firms	27	27
R^2	0.413	0.507
Adjusted R^2	0.309	0.413
Firm Fixed Effects	Yes	Yes
Year Fixed Effects	Yes	Yes

Robust standard errors in parentheses
* $p < .10$, ** $p < .05$, *** $p < .01$

The positive coefficient for industry median Q for the “Low Volatility Q” single-segment spin-offs implies that the investment ratio increases when industry median Q increases, further implying that the aforementioned spin-offs invest relatively more when experiencing superior investment opportunities. This is consistent with the coefficient for the overall sample as well as for larger spin-offs. The opposite is true for the “High Volatility Q” single-segment spin-offs. However, none of these coefficients are statistically significant and should therefore be interpreted carefully.

The coefficient for the interaction term *Industry Median Q * Pre* is negative for both groups, implying an increase in sensitivity to Q after the spin-off is completed. For single-segment spin-offs operating in low volatility Q industries, the coefficient is statistically significant on the 5 % level. Thus, it indicates that they experience a statistically significant improvement in capital allocation efficiency after completing a spin-off from their respective parent companies, which provides support for our hypothesis.

The operating profit ratio is statistically significant for both groups. For spin-offs operating in industries experiencing a low volatility in industry median Q the coefficient is positive and statistically significant on the 5 % level, implying that a 10 percentage points increase in operating profit ratio results in a 0.875 percentage points increase in investment ratio. For spin-offs operating in industries experiencing a high volatility in industry median Q the coefficient is negative and statistically significant on the 1 % level, implying that a 10 percentage points increase in the operating profit ratio results in a 0.155 percentage points decrease in the investment ratio.

The coefficient for the control variable net income is negative for both groups, indicating that single-segment spin-offs with a net income loss also experience lower investment ratios. However, the coefficients are not statistically significant and should therefore be interpreted with caution.

The adjusted R-squared is 0.309 and 0.413 respectively, indicating that the regressions for single-segment spun-off entities operating in industries with a low volatility in industry median Q explains 30.9 % of the variability in the investment ratio, and single-segment spun-off entities operating in industries with a high volatility in industry median Q explains 41.3 % of the variability in the investment ratio. Although rather similar to previous regressions, these adjusted R-squared are fairly higher.

5. Analysis and Discussion

5.1 Discussion of results and Limitations

Although the results from our study indicate that the 78 firms' sensitivity to investment opportunities increases, we find no statistically significant evidence in our thesis supporting that spun-off entities from diversified firms improve their capital allocation efficiency post spin-offs. However, statistically significant evidence is obtained specifically supporting that large spun-off entities and single-segment spin-offs operating in industries experiencing a low volatility in industry median Q, indeed improve their capital allocation efficiency post spin-offs. Our study contains several limitations possibly explaining some of the statistically insignificant results, which are discussed together in the following paragraphs.

5.1.1 Time period and sample companies

Compared to earlier research, such as Gertner et al (2002), our study is based on a more recent time period and thus a completely different sample of companies from various industries. Logically, market dynamics and characteristics have undergone tremendous changes between 1981-1996 and 2005-2016 (Malerba 2007). Such characteristics could consist of structural changes in corporate investment behaviour, entailing that companies disregard short-term changes in investment opportunities and rather invest more long-term, or volatile investment opportunities. For instance, Malerba (2007) explains that the fast-paced technological development has caused volatile internal movements in the majority of industries, causing many companies to struggle grasping intra-industry changes, which logically should reduce the sensitivity to investment opportunities. This might have hindered the firm's in our sample from correctly estimating and consequently acting on their investment opportunities. Thus, a possible limitation of our study is the observation period of three years pre- and post spin-off. In the case of a delay in the improvement of capital allocation efficiency post spin-off due to volatile investment opportunities, it might have been preferable to observe the spun-off entities during a longer time period such as five years pre- and post spin-off. However, this long time period would lack access to data since it is only possible to obtain data for the spun-off entities for a maximum of three years before their respective spin-off occurs.

Another possible explanation to our statistically insignificant results in hypothesis one could be found at firm and industry level in our sample. Compared to Gertner et al. (2002), our sample could consist of a larger ratio of more modern companies, primarily from the technological and pharmaceutical industry that has thrived since the beginning of the 2000s, instead of firms from traditional industries such as industrial and consumer. The structural investment behaviour in these two industry groups are very different. For the former, immediate profitability is not often the goal, but significant investments are however required along the way. This differs from the assumed predominant industries in Gertner et al.'s sample, where corporate investment is to a larger extent driven by profitability and free cash flow. The aforementioned information could contribute in explaining our statistically significant evidence supporting a negative correlation between operating profit ratio and investment ratio.

Hu (1995) found that excessive volatility might weaken the stock market's role as a forecasting mechanism and cause firms to systematically ignore volatile short-run changes and instead opt for long-term investment decisions. The US stock market was significantly more volatile during the period 2005-2016 than 1981-1996, which for our overall sample could have caused a reduction in sensitivity to changes in investment opportunities for spun-off entities, and thus help explain our statistically insignificant results for hypothesis one. However, the aforementioned findings by Hu (1995) along with Malerba's (2007) paper on fast changing industry dynamics could provide fundamental backing to our statistically significant evidence supporting an increase in investment efficiency for single-segment spun-off entities operating in industries experiencing a low volatility in industry median Q. Although providing an interesting research angle, estimating the investment opportunity volatility for each industry also acts as a limitation, being based on the rather weak assumption that all firms in a specific industry face identical investment opportunities.

5.1.2 Tobin's Q and different measures of investments

Using Tobin's Q as a proxy for investment opportunities is certainly a limitation to this study, since it assumes that all single-segment firms within an industry experience similar investment opportunities. Furthermore, it is assumed that firms should increase investments when industry Q increases. Since the book value is used as a proxy for "replacement value", the firm-specific Q ratios can also be affected by aggressive or conservative accounting. This could be consistent with research conducted by Whited (2001) who finds that the use of Tobin's Q indicates measurement errors. All of the aforementioned uncertainties might be explanatory factors for loss of significance in our results. However, should there be a measurement error when using industry median Tobin's Q it is likely present in both the pre and post spin-off periods, and one might therefore argue that the effect on the results only should be minor.

Furthermore, a firm's investments and capital expenditures are not solely driven by value-adding investments but may also consist of R&D or so called “maintenance capex”, which are investments necessary to keep the business going. Thus, there is an underlying behavioral difference between for example investing in an additional manufacturing machine to increase output and investing in a machine to replace a malfunctional one in order to maintain flat output levels. The inability to define the different investment types in our sample acts as a limitation, since it creates uncertainty regarding whether the companies are acting on present investment opportunities or if the investments consist of maintenance capex, bound to be carried out regardless.

Peters and Taylor (2017) find that Tobin’s Q, at firm-level, explains total investments well. However, compared to tangible capital, intangible capital adjusts more slowly to changes in investment opportunities. They further conclude that Tobin’s Q as a proxy for investment opportunities performs better in firms and years with more tangible capital. These findings highlight a limitation in our study, which is based on total investments, regarding the unavailability of information about the ratio of tangible/intangible investments in total investments each year.

5.1.3 Sample Size

Another potential limitation to our study is the small sample size, which is less than half the size of that used by Gertner et. al (2002). In order to examine the particular research questions, the data sample needs to be constricted according to certain criterias, which results in a large loss of spin-offs that occurred during the time period. Generally, when a study includes a small sample, a large effect is necessary to achieve statistical significance. Thus, the relatively small sample size might act as an explanatory factor to the loss of statistical significance in our results.

Another important limitation with regards to the sample is that we only investigate companies involved in spin-offs, and not a random sample. This results in a certain bias which makes it difficult to draw any general conclusions about the functionality of internal capital markets. Furthermore, only public spin-offs are examined which can bias and affect the results, as the inclusion of private companies might cause other implications.

Lastly, some companies conduct spin-offs with the primary motive to increase the capital allocation efficiency. Naturally, these companies should be considered more probable to achieve this, which creates a natural bias in the sample and consequently results in a difficulty to draw general conclusions about an increased capital allocation efficiency post spin-off as a generic effect. The aforementioned issue certainly acts as a limitation to the study and is furthermore difficult to control due to unavailability of information regarding the underlying reasons and motives to each spin-off.

5.1.4 Omitted Variables

The omitted variable bias is present in many statistical regressions, including ours, and acts as a possible limitation. There is a constant risk of existing factors that have an effect on the regressions but are not captured in the included variables. In order to mitigate the problem, we have included firm and time fixed effects as well as control variables that we expect to affect the dependent variable. However, there is always a risk that some important factors are left out.

6. Conclusion

This paper documents and discusses the change in internal capital allocation efficiency of spun-off entities, before and after completing spin-offs from their respective parent companies. Although indicating that the firms' sensitivity to investment opportunities, measured by industry median Tobin's Q, increases, we find no significant evidence in our thesis supporting that spun-off entities from diversified firms improve their capital allocation efficiency post spin-offs. However, statistically significant evidence is obtained specifically supporting that large spun-off entities and single-segment spin-offs operating in industries experiencing a low volatility in industry median Q, such as transportation, communication and wholesale trade, indeed improve their capital allocation efficiency post spin-offs.

Our findings indicate that the undertaking of spin-offs may have a minor positive effect on the internal capital allocation of the spun-off entities, being larger for entities with specific characteristics. Thus, one can argue that increased capital allocation efficiency of spun-off entities could impact the underlying value creation occurring in connection to spin-offs, taking the final form of abnormal positive shareholder return. Furthermore, the desired increase in investment efficiency might therefore act as an explanatory factor to the undertaking of spin-offs for diversified firms. However, our findings do not support the conclusion of a constant inefficient internal capital market within diversified firms, since firm-specific reasons for spin-offs are likely to have biased our sample with spin-offs operating in an inefficient internal capital market.

The research questions discussed in our paper, and the results obtained from our study, leaves room for future research to further examine the subject and seek answers to questions left unanswered by our paper. Firstly, the main question to investigate would be the possible reasons as to why spun-off entities would become more efficient in allocating their capital post spin-off. Could it be derived from more knowledgeable and smart decisions being made as an independent firm, with decision-making management closer to both the relevant operating market and stock market? Or does it stem from increased manager incentives in the independent spun-off entities? Furthermore, it would be of interest to examine the underlying reason for an increased improvement in capital allocation efficiency in specifically large spin-offs and single-segment spun-off entities operating in industries experiencing a low volatility in industry median Q, compared to its opposite group peers. Lastly, analysing and questioning the underlying bias, of not only our sample, but those of all papers examining spin-offs, would be of high interest - What are the characteristics of inefficient internal capital markets in diversified firms, that are causing the underlying rationale to conduct spin-offs?

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8. Appendix

Appendix 1: SIC Codes

The following table displays the classification of industries into SIC-codes.

Range of SIC Codes	Industry
0100-0999	Agriculture, Forestry and Fishing
1000-1499	Mining
1500-1799	Construction
1800-1999	Not Used
2000-3999	Manufacturing
4000-4999	Transportation, Communications, Electric, Gas and Sanitary service
5000-5199	Wholesale Trade
5200-5999	Retail Trade
6000-6799	Finance, Insurance and Real Estate
7000-8999	Services
9100-9729	Public Administration
9900-9999	Non-classifiable

Appendix 2: Variance Inflation Factors (VIF)

The following table displays all the VIF-factors for the variables in each regression.

	Reg 1	Reg 2 - Large	Reg 2 - Small	Reg 3 - High	Reg 3 - Low
pre	7.60	8.17	9.42	9.94	9.69
IndMedianQ	6.60	6.21	8.51	8.20	7.30
IndMedQ_pre	2.34	2.05	3.55	4.82	6.12
opprofit	2.27	3.33	2.51	2.98	2.75
netinc	2.43	2.66	2.47	5.92	2.33