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Shareholder Wealth Effects of Divestitures in the US Technology Sector: Evidence from 2012-2022

Author: J.K. Henriksson

Student number: 611126

Thesis supervisor: Dr. J.J.G. Lemmen

Second reader: Yashvir Gangaram-Panday

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Preface and Acknowledgements

This paper will conclude my master's degree at the Erasmus School of Economics. As a Master's thesis, it amalgamates theoretical principles with empirical findings, hoping to contribute insights to the existing body of knowledge in corporate restructuring. The journey of constructing this thesis has been intellectually rewarding and challenging, and every step in it has fed my interest in research methodologies and the world of corporate finance.

This journey has been a monumental commitment, and there are several individuals without whom this would not have been possible. I want to express my deepest gratitude to them.

I would like to express my profound appreciation to Dr. Jan Lemmen for his patience, insightful feedback, and mentoring throughout the process. It has been truly invaluable.

To my family, the endless support, encouragement, and understanding have carried me over the challenges. This achievement is as much yours as it is mine. Finally, to my close friends. Thank you for always believing in me.

Abstract

This thesis uses an event study methodology to examine the wealth effects of divestitures on parent firm shareholders in the US high technology sector from 2012 to 2022. The rapidly evolving nature of the high technology sector necessitates constant review and strategic divestment of loss-making assets, with reinvestment into those with positive future cash flow potential. Compounding this issue are recent policy rate increases, which heavily discount future cash flow prospects, thereby compelling companies to reassess their strategic decisions. While this study supports the consensus that divestitures create a positive wealth effect for parent firm shareholders, an in-depth analysis of various subsectors within the high technology sector reveals complexities diverging from this consensus.

Keywords: Corporate restructuring, High technology, United States, Divestitures, Event study, Wealth effect, Abnormal return

JEL Classification: G34

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List of Abbreviations:

AR abnormal return

CAAR cumulative average abnormal return

CAR cumulative abnormal return

CRSP The Center for Research in Security Prices

EMH efficient market hypothesis

FWER familywise error rate

IP intellectual property

M&A mergers and acquisitions

PE private equity

R&D research and development

TRBC The Refinitiv Business Classification

VIF variance inflation factor

WRDS Wharton Research Data Services

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Chapter 1 Introduction

The high technology industry has served as a critical driver of economic growth and job creation across US industries, with numerous sectors increasingly relying on it. In the decade succeeding the 2008 financial crisis, the US high technology sector witnessed consistent and robust expansion. Several critical factors have significantly shaped the status of the technology industry in the US market. These include the accelerated adoption of internet services and mobile devices, catalyzing the unprecedented demand for extensive data storage and sophisticated data analysis capabilities. Concurrently, transformative technologies like artificial intelligence have further fueled this technological evolution.

Moreover, as predicted by Moore's Law, the dramatic augmentation in microchip capabilities also plays a vital role in the industry's current trajectory. These cumulative influences underline the US market's increasingly digital and technologically driven landscape. Concurrently, mergers and acquisitions (M&A) activity has consistently remained at elevated levels within the industry.

In the high technology sector, M&As have emerged as a vital mechanism for traditional technology companies to achieve desired growth by acquiring essential intellectual property rights and knowledge, crucial sources of competitive advantage (Kallunki et al., 2009). However, as Donaldson (1994) highlighted, companies frequently over-diversify and engage in excessive acquisitions, resulting in asset inefficiencies and a loss of focus on core business activities. High-profile examples include the acquisition of VMWare by Dell Technologies for $60 billion in 2019, Mobileye by Intel for $15.3 billion in 2017, and Autonomy Corporation by Hewlett-Packard for $10.3 billion in 2011. Firms often encounter challenges during mergers, with the deals frequently eroding value due to shortcomings in the M&A process. As Meckl & Röhrle (2016) found in their meta-analysis regarding M&A deals, more than 50% of all M&A transactions are unsuccessful.

Strategic errors such as over-diversification or/and CEO empire-building will later necessitate refocusing the operations and divesting or disposing of redundant assets unassociated with a firm's core capabilities. Quickly adapting and being capable of reforming the strategy is particularly pertinent in the R&D-intensive high-technology sector, where promptly identifying, adopting, and executing a divestiture can ensure a company's survival and maintain an edge in the competition.

A corporate divestiture is a form of corporate restructuring and involves the modification of a firm's asset portfolio through the sale or spin-off of undesired assets. Although divestitures are often viewed as countermeasures against over-diversification, firms may also choose to divest a successful unit for strategic reasons, such as generating cash flow to support core operations or reducing their debt burden. As with other strategically motivated corporate transactions, the primary objective of divestiture is to maximize a firm's value. The prevailing consensus among scholars suggests that divestments yield positive announcement effects on the parent company's share price. The technology sector is characterized by high levels of R&D, which typically does not generate positive cash flows until innovations are successfully deployed in the future. As a result, prudent investors are advised to evaluate a corporation's dedication to mitigating diseconomies and its capacity to reinvest the resulting proceeds into its fundamental business operations.

This paper seeks to determine how the consensus aligns with technology sector divestitures over the years 2012 and 2022 by examining the following research question from the perspective of the divesting company's shareholders:

To what extent do corporate divestments create value for the parental firms' shareholders in the US high technology sector?

This study contributes to the existing body of literature by focusing on high-technology industry-specific divestiture announcement returns. The results are obtained by using the event study methodology. This paper also aims to contribute to the incomplete research on high-tech divestitures in the US market. We found that the aggregate high technology sample follows the consensus of positive wealth effects of divestiture announcements for the parent firms' shareholders. However, some of the subsectors under the high-tech category do exhibit results that depart from the consensus—emphasizing the importance of studying industry or business sector-specific announcement effects of divestitures.

We also find that the size of the divestiture is an important factor affecting the announcement returns as well as the financial performance of the parent firm measured by the net profit margin. We also conclude that in our aggregate sample, at least the weak form of the efficient market hypothesis holds due to insignificant post-announcement abnormal returns staying close to zero and statistically insignificant despite IT Consulting and Services subsample, which indicated negative post-announcement drift in abnormal returns.

The structure of this thesis is organized as follows: First, a review of existing literature is conducted to identify the consensus, which serves as the basis for formulating hypotheses to address the primary research question. Second, the process of sample collection, data sources, and a presentation of the statistical properties of the sample are provided. Third, an explanation of the applied methodologies - the event study approach, pairwise comparisons, and regression analysis with robust standard errors - is given, including their relevance to the proposed hypotheses. The results are then presented, followed by a discussion of the results, limitations of the study, and potential suggestions for future research.

Chapter 2 Literature

This chapter introduces the literature and reviews the findings regarding the announcement effect of divestitures. The existing literature has mainly focused on measuring overall stock price performance and neglected the industry-level scope in abnormal return measurements. We first briefly introduce the nature of the high-technology industry in the US. Then we present the history and background behind the divestitures and divestiture literature. Finally, we present the divestiture announcement wealth effects and the prevailing consensus regarding them and form relevant hypotheses that guide us in answering the main research question.

2.1 High-Technology Industry

The high technology industry in this thesis is defined based on Refinitiv Eikon’s Business Classification Standard (TRBC) definition. The industry is highly competitive, dynamic, and R&D intensive. The M&A activity in the technology sector is often driven by intellectual property and rights due to the intellectual capital-intensive nature of the industry (Alimov, 2017). Numerous companies in the industry see long R&D processes that tend to produce negative cash flows until the product gets to the market. Additionally, the R&D-related costs are expensed, and the value produced by R&D is challenging to value since it is not recorded in the balance sheet of a high-tech company. The results from R&D sometimes stay invisible until the company is acquired, and the value of R&D results is recorded in the acquiring company’s balance sheet as goodwill (Park, 2019).

Also, due to the high amount of intellectual property (IP) in the industry, M&As are standard practice for companies to grow and acquire complementary innovation to their asset base, and in the case of slow-growing or loss-making business units, they are divested. Between the years 2010 and 2020, a substantial proportion, approximately half, of corporations operating in the information sector engaged in at least one technology-related merger and acquisition (M&A). This trend evidences the strategic importance of consolidation and expansion within the dynamic technology landscape. (Jin et al., 2023).

Divestitures are an essential tool for tech companies to turn down old technology when adapting to technological development, and restructuring is needed to keep up with the change. For example, IBM divested its PC division to Lenovo in 2005 due to decreasing profits in the hardware market and willingness to focus more on the software and services business (Zhang & Yang, 2018).

History has shown that incumbent tech companies that fail to focus on the most core activities aligned with the current trends are setting themselves up for failure. Just like Nokia, an incumbent high-technology corporation, failed to adapt and adopt new technology. They refused to change along the new technology paradigm of touch screen technology and new operating systems until it was too late. It did not take long until Apple took the market-leading position with their iPhone, representing the new wave in handheld devices. Nokia’s 2013 divestment of the mobile phone business was reactively made to save the sinking company (Lamberg et al., 2021).

Definitions for the high-technology industry vary. This thesis follows Refinitiv’s definition. Refinitiv defines the high technology sector as consisting of eight distinct areas. Computers and peripherals, E-commerce / B2B, electronics, internet software & services, IT consulting and services, semiconductors, software, and other high technology.

The computers and peripherals sample includes companies like IBM, HP Inc, Dell Technologies, Apple, and other companies with business lines focused on producing computers and computer accessories. A computer peripheral device adds functionality to the computer system but is not essential to the system’s operation. These devices include data storage devices, interactive terminals, and input/output devices (Bingham, 1983). In 2022 the US was the largest market for this subsector (The Business Research Company, 2023).

The E-commerce B2B sector comprises high-technology companies with businesses in the B2B space. For example, Google has been active regarding website building, domain, and email marketing services. This subsector experienced quick expansion during the adaptation of the world wide web at the beginning of the 21st century when firms started to execute interfirm transactions relying on electronic systems and applications (Dai & Kauffman, 2002).

The electronics subsample consists of business activities focusing on electronics development and production. The US electronics industry is an essential source of innovation among the other high-tech industries for the US economy. The US electronics market has experienced stiff competition against foreign manufacturers throughout its existence. The trend in the past has been that unskilled and semiskilled employees in the industry have been likely to lose their jobs due to technological advancement, imports, and production being transferred offshore (Alic & Harris, 1986). An example of the companies found in this subsample is VIDE, a manufacturer of electronic display solutions and systems for a broad market of medical, military, industrial, and aerospace applications. Another example is HWCC, an American distributor of electrical and mechanical hardware products for industrial and commercial markets.

Internet software and services involve companies like Yahoo, Uber, Zynga, and Applovin. These companies have business in different types of internet software and service productions. The industry is constantly changing due to changes in tools, practices, automation, and scalability (Laato et al., 2022). Additionally, cloud services are an essential aspect of the software and services business since, increasingly, many companies are taking their on-prem computing solutions to the cloud, which has implications for the firm’s asset base and cost structure (Nezami et al., 2022).

The IT consulting and services subsector of high technology provides the consultation and services layer around high technology products. These activities are system integration, made-to-order application development, and maintenance. These services are essential to help organizations to leverage their technology assets to support their business operations. As Kumar et al. (2017) noted, this industry has matured well in the past 20 years due to most firms' need for external expertise in their IT solutions.

The semiconductors subcategory comprises semiconductor producers such as Intel, GSI Technology, and OSI Systems. Semiconductors have been and are fundamental to technological development and a source of economic growth and competitive advantage across different industries. Semiconductors as a product are often compared to natural resources such as oil and gas due to the expertise in this sector being condensed into a few facilities globally. That has led to a strong political aspect taking its place in this industry, and world politics have started to gather around the fact that the nation or region that controls the competitive edge in semiconductors will also have an edge in the global political arena. The US semiconductor industry has problems with manufacturing being cheaper and more accessible in Asia, and the US venture capitalists have been redundant to take risks in the US semiconductor businesses and lack of knowledgeable workforce in the field of semiconductor manufacturing (Thomas, 2022).

The software sector overlaps with the internet software and services, but it is a broader definition for companies that focus on developing, maintaining, and publishing software. These companies can do operating systems, tailored industry-specific software, or Commercial-Off-The-Shelf (COTS) software products (Gnanasankaran et al., 2021).

The other high technology presents a minor proportion of the aggregate high-tech sample. It consists of companies that do not fit into the categories introduced above. One example from this sector is General Cable Tech Corporation which announced the divestiture of its US automotive ignition wire business in 2016 for $71 million. This divestiture was aimed at reducing outstanding borrowings of the company (Business Wire, 2016).

2.2 Divestitures Background

Between the 1960s and 1970s, US firms tended to diversify extensively. Instead of encouraging internal growth, buying growth from outside was thought to be more accessible and maintain a firm's ability for self-preservation among the competitors. Most strategic choices were explainable by the characteristics of the post-WWII era: high uncertainty, conservative strategies, low debt, and high retained earnings. These rather conservative characteristics led to a high level of unused debt capacity and excess liquid assets that the managers used for diversification. Things changed in the 1980s when institutional investors started to increase their assets under management and began to gain territory from the retail investor dominance in corporate ownership (Fichtner, 2019). The institutional investors were more financially sophisticated and were acting more rationally. They lacked loyalty to a particular stock and instead focused on returns and a sufficient level of diversification in their portfolio. They had low tolerance toward companies holding underutilized assets. This change in the paradigm forced companies to consider the increased level of financial literacy in the market in their strategies. Extensive diversification was no longer considered as virtuous as in the previous decades (Donaldson, 1994).

In the 1980s, many hostile takeovers were carried out due to many companies with a high level of underutilization due to excessive diversification. Kaplan & Weisbach (1992) found that divestitures are four times more likely to happen if the divested asset is unrelated to the core business activities, therefore supporting the theory that companies were guilty of acquiring inorganic growth too far from their core competencies. In 1994, Donaldson challenged the idea of outside intervention being the only way to regain the lost efficiency in the economy. He argued that firms could improve their efficiency through a voluntary restructuring where the underutilized assets were divested, and the proceeds were invested back into the core business operations and assets. Brauer & Wiersema (2012) identified two major divestiture waves from 1993 to 2007 in their sample. The first occurred between 1996 and 2000, and the second between 2004 and 2007.

From 1993 to 2007, the value of divestiture activity multiplied from under $100 billion to $500 billion, and its proportion of total M&A activity in the US has been around a third of all M&A activity. After the 2008 global financial crisis, the importance of divestiture activity has been better acknowledged among investors, realizing that divestitures tend to carry much greater ambiguity about the mechanisms of wealth creation, underlying motives, and strategic reasoning (Brauer & Wiersema, 2012). That ambiguity and lack of thorough understanding make it harder for investors and analysts to evaluate the long-term effects of divestiture for a firm compared to mergers and acquisitions.

2.3 Divestiture Announcement Wealth Effects

In complete and perfect markets, a divestiture should only positively affect the firm's value if the market perceives divestiture as a value-increasing transaction (Miles & Rosenfeld, 1983). According to the consensus, voluntary divestitures carry positive abnormal returns that increase the divesting companies' shareholder wealth, as presented in Table 1. Boudreaux (1975) found in one of the earliest divestiture studies that capital markets seemed to react quickly and appropriately to the information that the divestiture announcements carried. He concluded that if voluntary divestments are considered the same as other financial management decisions, such as M&A decisions, divestments will lead to a shift in shareholder wealth. Boudreaux also studied involuntary divestitures that were found to have adverse wealth effects due to their different nature being usually enforced by the anti-trust authorities, where operating cash flows are exchanged for less than their present value leading to the destruction of value.

More recent studies like Teschner & Paul (2020) found a 1.33% cumulative average abnormal return (CAAR) on the announcement date in the DACH area divestitures. Benou et al. (2008) studied high-tech divestitures from the sellers' and buyers' perspectives. Their high-tech definition departs from this thesis, and their sample consisted of divestitures between 1981 and 2001. They found that divestitures are value-enhancing for the sellers when measured over the -1 to +1 event window.

In order to present a comprehensive outlook of the literature, Table 1 gathers the divestiture literature and presents the conclusion of the wealth effects of studies from the parent firms' shareholders' point of view. Notably, all the publications report a positive wealth effect; therefore, we expect similar conclusions in this thesis. Therefore, the first hypothesis follows:

H1 = ***High technology divestiture announcement leads to positive abnormal returns on the share price of the divesting firm.***

Table 1: Digest of Event Study Literature on Divestiture Announcement Effects

Author(s) (Publication year)	Period	Sample size	Data type	Region	Benchmark method	Wealth effect
Boudreaux (1975)	1965 - 1970	169	Daily	UK	Market Model	Positive
Miles & Rosenfeld (1983)	1962 - 1980	55	Daily	United States	Mean Adjusted Return	Positive
Rosenfeld (1984)	1963 - 1981	97	Daily	United States	Mean Adjusted Return	Positive
Alexander et al. (1984)	1964 - 1973	53	Daily	United States	Market Adjusted	Positive
Hearth & Zaima (1984)	1979 - 1981	58	Daily	US	Market Model	Positive
Jain (1985)	1976 - 1978	1107	Daily	United States	Market Model	Positive
Zaima & Hearth (1985)	1975 - 1982	79	Daily	United States	Mean Adjusted	Positive
Skantz & Marchesini (1987)	1970 - 1982	37	Monthly	United States	Market Model	Positive
Afshar et al. (1991)	1985 - 1986	178	Daily	UK	Market Model	Positive
Brauer & Schimmer (2010)	1998 - 2007	160	Daily	Global	Market Model	Positive
Teschner & Paul (2020)	2002 - 2018	393	Daily	DACH Region	Market Model	Positive

Continuing with the theory of signaling effects, an essential part of the finance literature. The company's strategic and financial decisions are thought to contain information not directly disclosed to the market, that the market participants will interpret according to available information and their rationale. We could argue that a strongly performing company announcing divestiture will signal that the divestment decision is a proactive operation made under careful strategic reasoning, leading to more efficient core operations and increasing the firm's performance. This type of signal would lead to an increase in the stock price.

Correspondingly a poorly performing firm carrying out a divestiture would signal that the divestiture is done primarily or solely due to financial distress. Hearth & Zaima (1984) divided their sample into two categories: firms with strong financial performance and firms with poor financial performance. They found that better-performing firms have larger CARs, which are also more statistically significant. Therefore, the second hypothesis follows:

H_2 = A parent firm's financial performance has a positive relationship with abnormal returns at the announcement.

Miles & Rosenfeld (1983) found that the size of the divestiture affects the announcement returns. They concluded that large spin-offs positively influence the share price more than small spin-offs. The large spin-offs led to 2.41% higher returns over the 0,1-event window than small spin-offs. The abnormal return stayed positive up to 60 days after the event, whereas the small spin-offs quickly turned into negative abnormal returns during the same period. They used 10% as a cut-off value for defining a large divestiture. If the divestiture deal size was more than 10% of the divesting firm's market value, the divestiture was considered large, and if the share was less than 10%, it was considered small. This cut-off value is somewhat arbitrary. Hearth & Zaima (1985) used eight percent in a similar study where they also found a positive relationship between relative deal size and the divesting firm's wealth effect.

H_3= *The size of divestiture has a positive relationship with CARs at the announcement.*

Since the high technology sector consists of sub-sectors that arguably have differences in capital structures and asset base characteristics, the interest transfers to measuring how much there is a difference between these groups. The factors affecting the capital structures involve the maturity of the subsector, the capital intensity of the production and operations, and the riskiness of the sector (Sheehan & Graham, 2001). One could argue that companies in the software sub-sector carry different financial structures and strategies than those in the semiconductor sector, and the nature of divested assets from the company's balance sheet will affect the market reaction and, therefore, abnormal returns at the announcement.

H_4 = *The behavior of abnormal returns significantly varies across different subsectors.*

2.4 Persistence of the Abnormal Returns

The hypothesis regarding market efficiency will be challenged if the announcement effect stays visible long after the announcement. In tech companies, the divestment of unsuccessful or unrelated business units might increase the company value if it is seen that the received capital can be invested profitably. Bernard & Thomas (1989) studied the post-earnings announcement drift effect and found that stock prices tend to drift in the direction of the announcement sentiment. Hence, if the divestiture announcement is viewed positively, the stock price may not instantaneously embody the entire effect. It was discovered that most of the drift happens within 60 days post-announcement. If persistent, this effect contradicts the efficient market hypothesis in its semi-strong form, an essential assumption in event studies.

The persistence and drift are measured according to earlier studies. Miles & Rosenfeld (1983) used the following event windows: +2 through +10 and + 11 through +60 to measure cumulative average abnormal returns in their sample. These two periods produced positive results, but neither of the results of the two event windows was statistically significant. The same insignificance was found when they split the sample into groups of small and large divestitures. The following hypothesis will be tested with the aggregate industry data. In 2012 Fu & Huang (2016) studied the persistence of long-run abnormal returns after corporate stock transactions. They argued that institutional ownership, algorithmic trading, and reduced trading costs have led to a more efficient market where investors can quickly incorporate the new information thoroughly, which is then reflected in the equity prices. Our goal is to check if the assumption of a semi-strong form of efficient markets (Fama, 1970) holds in the case of our scope of study. Therefore, the last hypothesis will be that no significant post-announcement CARs persistence exists in the aggregate high-tech sample.

H5 = The stock prices do not reflect significant post-announcement CAR persistence in the direction of the announcement effect.

Chapter 3 Data

In this chapter, the data collection method and sample characteristics are introduced. The different subsectors in the high technology sector are introduced with brief examples. Then we represent descriptive statistics for the variables involved and state the nature of limitations found in the gathered data.

3.1 Sample

The divestiture data is gathered from the Thomson Refinitiv database using the equities screener tool. The divestment data is found under the M&A data category in the advanced search tab. The data consists of US high-technology companies that have done divestiture from January 1st, 2012, to December 31st, 2022. The high-technology economic sector is defined by Refinitiv's Business Classification Standard. It consists of different high-technology sub-industries that we also refer to as subsectors. The subsectors are listed in Table 3.

The following criteria are applied to the advanced search tool. The announcement date of the divestiture must be in the period 1st of January 2012 – 31st of December 2022. After this criterion, we define that the transaction must have a divestiture flag, and the deal value must be over one million USD. Since we focus on the US market, the target ultimate and immediate parent must be a US company. We also want to ensure the public status of the ultimate and immediate parent of the target company. The target's ultimate parent and immediate parent macro industry is set equal to high technology. We also filter out financial firms due to their M&A and divestitures activity, often driven by non-strategic reasons. The deal status is added to the dataset where the deal completion is set as complete and unconditional.

To verify the seller's identity in the case of a more complex ownership structure, we include the filter that the ultimate and immediate parent can be either public or subsidiary. Suppose the ultimate parent is public, and the immediate parent is a subsidiary. In that case, we identify the ultimate parent as the seller, and if both are public, we identify the immediate parent as the seller. After checking the ownership structure, we conclude that the ultimate parent and immediate parents are listed under the same ticker in our sample. Therefore, they can be considered as one entity for the sell-side of the divestiture.

Additional data validation was done by cross-checking the target ultimate parent identification info in the CRSP equity database with the search tool provided by WRDS. If the ultimate parent was found from CRSP, it was kept in the sample. If not, then omitted completely. This data cleaning was done to mitigate quality issues that were present in the dataset obtained from Refinitiv Eikon. For example, some ultimate parents had the wrong tickers or CUSIP codes. These were validated and corrected with the CRSP information. If the correction was not possible, then the incorrect data was omitted. Lastly, if the same company announced two different divestitures on the same date, the divestitures were merged and reported as one observation.

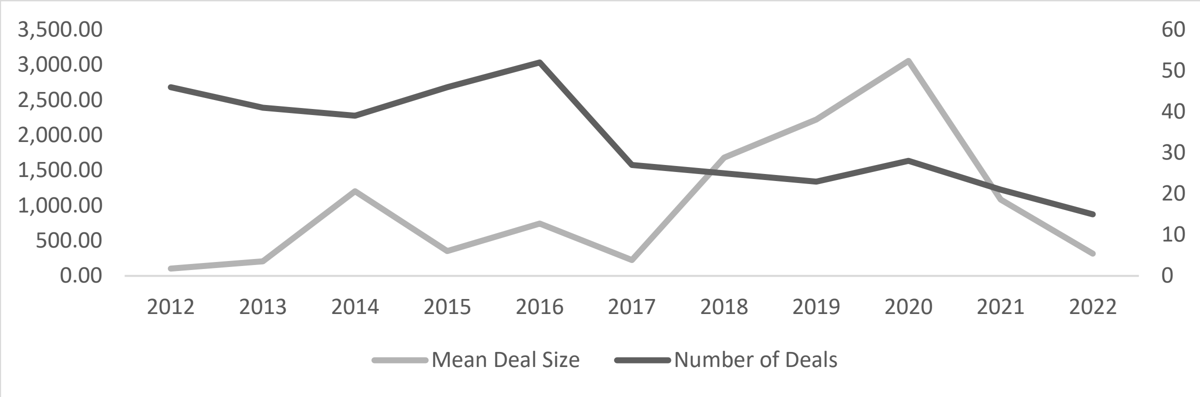
Table 2: Sample Selection

Note. The CRSP validation was done to verify the seller's identity and the integrity of the data. If the observation obtained from Refinitiv Eikon did not match the CRSP database, the observation was omitted from the sample.

Filter	Number of announcements
Announcement date: 1.1.2012 – 31.12.2022	591130
Divestiture Flag: True	166425
A deal value greater or equal to 1 million	65462
Target Ultimate and Immediate Parent Nation: United States	11406
Parent firm’s Public Status: Public	5937
Parent firm’s Macro industry: High technology	515
Deal status: Completed and unconditional	447
CRSP validation match	410
Two divestitures on the same date by the same parent merged	402
Non-missing return data in CRSP:	
Market-adjusted model sample	349
Market model sample	314

Figure 1 depicts the general trend that the number of divestitures steadily decreased between 2012 and 2022, but the average deal value increased. In 2018 MelCap Partners released an article that considered the decrease in the US divestitures after 2014 mainly due to the imbalance in the M&As that has led to an elevated valuation multiple across the US industries. One could argue that FED’s quantitative easing has driven the valuation multiples, and bidders have become increasingly competitive over quality assets, leading to decreasing deal numbers but increasing deal size. The drop in the number of deals and deal size during 2020 could be attributed to the beginning of the Covid-19 pandemic that caused industry and market-wide disturbance across the globe. During the first year, companies searched for internal or traditional ways to maintain their operational capacity. However, in 2021, companies still challenged by the economic disturbance started implementing divestiture operations to restructure and rescale their operations to cope with the market downturn. As a result, we expect that many companies were forced to conduct divestitures after searching for and using alternative methods, such as increased debt capacity, to fuel their pre-pandemic scale of operations (Kooli & Lock Son, 2021). This fact is also visible in the high-technology sector in Figure 1, where the negative slope of the number of deals line levels out a bit during 2021.

Figure 1: Average deal size and number of deals in the US high-tech sector between 2012 and 2022



3.1.1 Subsectors

The definition of high-technology by Eikon Refinitiv falls into eight different subsectors that we found adequately represent the high-technology industry. The divestitures' average deal dollar values and the number of observations on each category are listed in Table 3, ordered by their mean deal size. Computers & Peripherals is the largest measured by the mean deal size, primarily due to a few relatively large deals in this industry, and the electronics sub-sample consists of relatively small divestitures.

Table 3: Eikon Refinitiv High Technology Subsectors and Average Deal Sizes

Subsector	Mean Deal Size in USD	N
Computers & Peripherals	2,681,661,612	65
E-commerce / B2B	1,973,955,310	22
IT Consulting & Services	481,374,989	48
Semiconductors	481,016,895	94
Software	420,814,757	58
Internet Software & Services	414,024,864	65
Other High-Technology	201,234,331	10
Electronics	144,411,450	40

3.1.2 Variables of Interest

In regression, we use the two-day $CAR_{0,1}$ as a dependent variable; it includes the day zero and the succeeding day. This variable will be under our primary focus throughout the analyses and on the cross-sectional since we expect it to capture most of the announcement returns according to the consensus.

The drivers of the CARs obtained are then evaluated by defining independent variables that are derived from the financial literature. We use conventional financial ratios to test the link between CARs and financial performance. We include net profit margin as a measure of profitability, sales to working capital as a measure of financial efficiency, current ratio as a liquidity metric, and book-to-market value as an indicator of a firm's relative valuation.

The net profit margin is a profitability ratio (NPM). That is the proportion of money left after all the expenses are deducted from the revenue. The higher the net profit margin, the better the company can generate net income from its sales, indicating operational efficiency (Handayani & Winarningsih Zarkasyi, 2020).

Second is the sales to working capital (SWC), which measures a firm's operational efficiency, where working capital is defined as the current assets minus current liabilities. In short, a higher ratio means the firm can generate more sales per unit of working capital. We expect that a firm with a lower SWC will experience a higher announcement effect since, according to the consensus, the divestiture could be motivated by an increase in the efficiency of the operations.

The third regressor is the current ratio (CR), a liquidity measurement used to evaluate a firm's ability to pay back its debt. The ratios are included due to their contribution in testing hypothesis 2 about financial performance driving the firm's CARs at the announcement. A high current ratio could indicate that a firm's action is motivated by strategic implications rather than financial distress.

The following variable of interest is the book-to-market ratio (BM). It is defined by the book value of equity divided by the market value of equity. The ratio is extensively studied in the finance literature and is usually used to identify the under or overvaluation of a firm. The book-to-market effect is found to be a significant explanatory variable in the stock return cross-sectional analyses. High book-to-market stocks are typically called value stocks and have been found to earn positive excess returns, whereas low book-to-market stocks are related to growth firms that are found to earn negative excess returns (Cakici & Topyan, 2014).

The book-to-market variable becomes increasingly attractive for our study. Since high-technology companies are a great source of innovation and R&D heavy, they possibly hold intangible assets that are not always reflected in the firm's intrinsic value. For example, for a company that has developed new technology and has expensed its R&D costs, the value of the new technology is not recorded on the balance sheet, and therefore the book value is lower than its market value. The value is not visible until another company buys the firm, and the value of new technology enters into the acquiring company's balance sheet as goodwill (Park, 2019). Also, as the high-tech sector tends to employ a highly-skilled workforce, the value of the human capital is not measured in the book value. One could argue that the difference between book and market value is a proxy for intangible asset value. The value of high-tech firms and, therefore, their acquisition and asset divestiture price depends on intangible capital, as argued by Peters & Taylor (2014). We want to capture and measure the magnitude of the book-to-market effect by including the BM ratio.

As we want to test hypothesis 3 about larger deal value leading to more positive CARs at the announcement, the relative size of the transaction to the firm size is calculated as a dummy variable, and the differences between the large and small divestitures will be compared. The market value is obtained from the Refinitiv Eikon database and matched to the divestiture announcement date. We also control the firm's market value at the time of the divestiture to the regression with the market value regressor, which is a natural logarithm of the firm's market value at the announcement date.

Lastly, we included subsector and year dummy variables that control for the year-to-year and subsector differences. The year dummy will catch year-to-year differences that might result from shifting macroeconomic conditions, technological advancements, and or changes in regulation during the sample period. The subsector dummy will control the possible heterogeneity between different subsectors. Different types of risks, growth prospects, regulatory impacts, and general investor sentiments towards specific subsectors may cause general differences that we want to control with the subsector dummy.

Table 4: List of Dependent and Independent Variables

Note. Dependent and independent variables used in the regression analysis in Part 5.5

Variable	Symbol	Definition
Dependent variables		
$CAR_{0,1}$	$CAR_{0,1}$	Two-day CAR with an event window from day 0 to 1
Independent variables		
Net profit margin	NPM	Net profit divided by revenue
Sales to Working Capital	SWC	Sales divided by working capital
Current ratio	CR	Current assets divided by current liabilities
Book to market	BM	Book value divided by market value
Large deal dummy	Large_deal	Dummy variable when the divestiture is equal to or more than 10% of a firm's market value
Market value	ln_MV	Natural logarithm of a parent firm's market value at the announcement
Subsector dummy	Subsector_K	Dummy for divesting firm's subsector
Year dummy	Year_K	Dummy for announcement year

The summary statistics for the variables employed are displayed in Tables 5 and 6. The tables report the descriptive statistics for the variable of interest obtained with the market and market-adjusted models, respectively. We include the number of observations, mean, standard deviation, min, median, max, skewness, and kurtosis. In the case of severe outliers, the variable is winsorized with 1% and 99% cut-offs. This will mitigate the effect of outliers being influential in the regression model. We winsorize the net profit margin (NPM), sales to working capital (SWC), Current Ratio (CR), book to market ratio (BM), and the dependent variable $CAR_{0,1.}$ The original pre-treated descriptive statistics are included in Appendix A in tables A1 and A2. The market model specification involves fewer observations than the market-adjusted model due to the lower amount of CARs available due to the omittance of overlapping divestitures.

Table 5: Descriptive Statistics for the Market Model Specification

Note. Dependent and continuous independent variables for regression models 1A and 1B. The market value is the natural logarithm of the MV. Net Profit Margin (NPM), Sales to Working Capital (SWC), Current Ratio (CR), and Book to Market (BM) variables are winsorized at 1% and 99%. The variables are defined in table 4.

Variable	**Obs.**	**Mean**	**Std. dev.**	**Min**	**Median**	**Max**	**Skewness**	**Kurtosis**
Dependent variables								
$CAR_{0,1}$	224	0.0197	0.0899	-0.2130	0.0049	0.3160	1.0011	5.9333
Independent variables								
NPM	224	-0.1107	0.5960	-4.0703	0.1680	0.3635	-5.1622	32.9095
SWC	224	7.2356	13.3040	0.0289	3.8544	91.2138	4.9091	32.0823
CR	224	2.6086	2.3444	0.9703	1.8616	23.9345	4.6851	35.8901
BM	224	0.5439	0.4170	0.1654	0.4201	2.3760	1.8048	7.2885
Ln_MV	224	7.5099	2.5420	1.5994	7.5099	13.1837	0.0990	2.3838

Table 6: Descriptive Statistics for Market-Adjusted Model Specification

Note. Dependent and continuous independent variables for regression models 1A and 1B. The market value is the natural logarithm of the MV. Net Profit Margin (NPM), Sales to Working Capital (SWC), Current Ratio (CR), and Book to Market (BM) variables are winsorized at 1% and 99%. The variables are defined in table 4.

Variable	Obs.	Mean	Std. dev.	Min	Median	Max	Skewness	Kurtosis
Dependent variables								
CAR0,1	264	0.0211	0.0869	-0.2129	0.0062	0.3160	0.9438	5.9973
Independent variables								
NPM	264	-0.1276	0.6865	-4.8152	0.0174	0.4269	-5.2523	33.1454
SWC	264	7.3342	13.3143	0.2210	3.8670	100.6049	5.2840	34.8191
CR	264	2.4428	2.3792	0.4087	1.7385	23.9449	4.4262	31.4362
BM	264	0.5349	0.3966	0.0165	0.4271	2.3760	1.7869	7.6747
Ln_MV	264	7.5723	2.4811	1.5994	7.6261	13.1847	0.0563	2.3752

3.1.3 Data Limitations

There are limiting factors when using historical stock price data. First, many databases do not keep historical price data of delisted stocks. Indicating there will usually be survivorship bias to some degree. Survivorship bias potentially affects the conclusion because the time period could have had distressed firms that executed divestiture operations, but they ended up omitted from the sample due to missing return data.

Second, applying the market model to the event study methodology requires us to calculate returns during the estimation window. Sometimes this is not plausible due to missing stock price data, and the reasons for the missing data are often not evident. The availability issues were present both in the Eikon Refinitiv and CRSP databases. The workaround for the missing returns is to use a market-adjusted model that does not require us to use the estimation window and could lead to fewer observations being omitted. In this study, we use both the market model and the market-adjusted model for the sake of robustness. The sample size is indicated with each test.

Due to the missing observations with the market model, the number of announcements will vary due to some observations being dropped from the sample when the WRDS tool is run over the selected estimation window. The number of announcements per CAAR value is specified in the results tables. The same limitations regarding historical data occur when querying market value and financial ratio data. We encountered a few divestitures that did not have market value data available, and these observations were dropped from the dataset.

For the cross-sectional regression analysis, the financial data availability issues limited the number of observations that could be used in our regression model specifications. The announcements that had missing financial data were omitted. The amount of observations with market model data is reduced to 224 observations and 264 with the market-adjusted model data.

Chapter 4 Methodology

This chapter introduces and links the event study methodology (MacKinlay, 1997) to the hypotheses introduced in this thesis and approaches to measure the abnormal and cumulative abnormal returns at the divestiture announcement date. We specify the regression models used to inspect the different factors potentially affecting the announcement returns. Since we also have subsamples, we are willing to run pairwise comparisons to identify the potential differences with statistical inferences. The Kruskal-Wallis test (Kruskal & Wallis, 1952) tests the null of equal medians. If the null gets rejected, Dunn's test (Dunn, 1964) produces pairwise comparisons, indicating the sign and significance of the distinguished comparisons between each group.

4.1 Event Study

We use the event study methodology to answer our hypotheses. Event study methodology is a widely used tool by financial economists to capture the impact of financial events on the firms' stock price. It relies on the assumption of the efficient market hypothesis (EMH). This theory, in its semi-strong form, dictates that stock prices reflect all the publicly available information from the past, and the market immediately reacts to new information, where market participants trade until the new information is fully incorporated into the stock price. One step further, we have a strong form of EMH, where all of the public or private information is available to all market participants. If the strong form holds, we should not see an indication of abnormal returns before the event date. Fama (1970) concluded that, in general, the EMH holds well.

The second assumption is that the parent firm's executive level is acting in the best interest of shareholders. This assumption means executives do not undertake negative NPV transactions that destroy shareholder wealth. Examples of violations of this assumption stem from agency theory, where there is a natural conflict between shareholders and managers because individuals choose actions to maximize their own utility (Hope & Thomas, 2008). However, divestitures are under great scrutiny by the shareholders, and if the managers undertake value-destroying divestiture decisions, then shareholders may attempt to replace the managerial level (Jain, 1985). Therefore, the second assumption is reasonable.

For testing Hypotheses 1,

High technology divestiture announcement leads to positive abnormal returns on the share price of the divesting firm with event study methodology.

The divestment's wealth effect is measured by calculating average abnormal returns (AARs) at and after the announcement date and then aggregating AARs to two-day $CAAR_{0,1}$ by summing the day zero AAR_0 and day +1 AAR_1 together. AAR is the residual that the model cannot explain during the announcement. We do the same measurements for the aggregate sample and subsamples to test hypothesis 1 but to produce metrics for testing hypothesis 4, where we try to find evidence that the abnormal return behavior at the announcement varies between different subsectors.

The models used in the return calculation are the market and the market-adjusted models. Alternative models, such as CAPM or Fama-French models, have also been used by scholars. However, we do not consider using the CAPM or Fama-French multifactor models due to their marginal explanatory power over the market model (Mackinlay, 1997). According to the consensus, we expect to observe positive two-day CARs at the announcement date, which would lead to acceptance of hypothesis 1 of positive abnormal returns of the divesting firm.

4.1.1 Event Windows

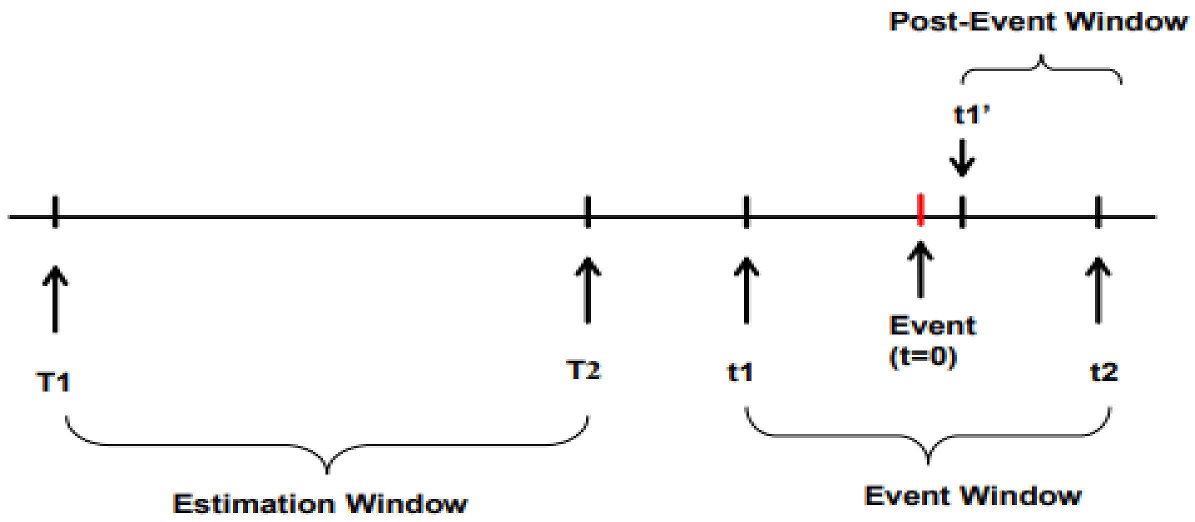
The first step is to identify event windows. The event window outlines the time frame around the divestiture announcement. If the announcement occurs near or after market closing, it is advisable to include the next day in the event window to capture the full impact of the announcement (MacKinlay, 1997).

Previous studies have suggested different lengths for event windows. A longer event window before the announcement is able to capture potential information leakage, while an event window extending beyond the announcement can help examine the potential persistence of the abnormal returns. If found, such persistence is a violation of the EMH, which undermines the precision and reliability of the methodology since the complete magnitude of the wealth effect is spread out and goes against hypothesis 5 that the stock prices do not reflect significant post-announcement CAAR persistence in the direction of the announcement effect.

We include both pre- and post-announcement event windows as preparation for possible pre- or post-announcement complications. While our hypotheses are not concerning pre-event information leakage, we want to test its existence since if some of the announcement effects occur before the event, it can alleviate the immediate announcement effect measured by the two-day $CAAR_{0,1}$.

Following MacKinlay (1997) and De Jong (2007), we index the announcement dates as t=0. Then t1 and t2 represent the start and end of the event window. It is typical to set the event window length to at least accommodate the succeeding day of the t0. The inclusion of succeeding days captures the effects of divestiture announcements that are done close to or after the market closure (MacKinlay, 1997). The post-announcement window starting at t1' in Figure 2 captures the possible drift of the abnormal returns that might indicate the persistence of the wealth effect and provide evidence for or against Hypothesis 5.

Figure 2: *Timeline of an event study. Adopted from de Jong (2007)*



We inspect the existing event study literature to specify the lengths of event windows. No consensus exists on which event windows are the right choice. Scholars seem to use first a more extended event window spanning up to months before the announcement and extending multiple days beyond the announcement. When the extended window has provided general properties about the behavior of abnormal returns, scholars define more detailed and shorter event windows to test different pre-, at, and post- announcement effects. For example, Miles & Rosenfeld (1983) used an event window ranging from -120 days to +60 days relative to the event date to study stock price movements well before the event date and observe post-event stock price behavior. Similarly, Afshar et al. (1991) utilized a -40 to +40 event window to study abnormal returns around the event date. Miles and Rosenfeld used 0 to +1, +2 to +10, +11 to +60 event windows, and others used similar event windows but slightly varied lengths.

We adopt a hybrid event window of Miles & Rosenfeld (1983) and Afshar et al. (1991) for the extended window. We use a -60 to +60 days event window to measure abnormal returns around the announcement. For a closer inspection, we define -35 to -1 days and -3 to -1 event windows to inspect pre-event abnormal returns. These event windows are based on the nature of our data, which shows that CAARs start to rise around 35 days before the event in Figure 3.

We use two immediate event windows, 0 to +1 and -3 to +3, to measure the abnormal returns at the implied announcement date. The first two-day window is supposed to capture the immediate effect of the announcement, capturing the event day and the next day. The following seven event window provides robustness and prepares for delayed or other event day complexities, such as the delayed effect that is not observed immediately with the two-day event window.

Hypothesis 5 is about testing the announcement effect's persistence:

H5 = The stock prices do not reflect significant post-announcement CAR persistence in the direction of the announcement effect.

According to Miles & Rosenfeld (1983), two event windows, -2 to +10 and +11 to +60, are meant to capture the possible CAAR persistence that would indicate violation against weak-form market efficiency and therefore lead to rejection of hypothesis 5. We include the post-announcement $CAAR_{-2,10}$ and $CAAR_{11,60}$ estimations to the aggregate and subsample CAAR calculations to study if the abnormal return is persistent in the aggregate or the subsamples.

4.1.2 Estimation of Normal Performance

The second step in the event study methodology is to estimate the normal performance. There are a few commonly used options for the normal performance measurement. The market model is commonly used due to its simplicity and usability. Another commonly used measurement is the market-adjusted model. It is also called a restricted model since the intercept variable is constrained to zero and β constrained to one (Mackinlay, 1997). The market-adjusted model has benefits due to its simplicity and resistance against estimation window complications, such as overlapping announcements for the same company during the estimation. However, we should expect the market model to produce a more precise normal performance estimation since it accounts for the proportion of variation of the stock return related to the market's return and potentially reduces the variation in the ARs (MacKinlay, 1997).

The market model links any given security's return on the market portfolio:

$$R_{it} = \alpha_i + \beta_i R_{m_t} + \varepsilon_{it}$$
$$E(\varepsilon_{it} = 0) \quad \text{var}(\varepsilon_{it}) = \sigma^2_{\varepsilon_t} \tag{1}$$

Where R_{it} and R_{m_t} are the period-t returns on security i and the market portfolio, respectively, and ε_{it} is the zero mean disturbance term, α_i, β_i and $\sigma^2_{\varepsilon_t}$ are the parameters of the market model, which are estimated during the estimation window. The market return is proxied by the CRSP value-weighted index, which has been the standard choice for US equities research (De Jong, 2007).

A notable concern with the market model and its estimation window is the possibility of other events occurring concurrently that may introduce bias into normal performance (Patton et al., 2003). In our dataset, several companies had done divestitures in the short term and had overlaps between divestiture announcements and estimation windows. Such events have the potential to impact the robustness of the abnormal return estimations. In instances where divestiture announcements for the same firm overlapped, we retained only the first announcement, discarding consecutive announcements that had the first announcement overlapping inside of its estimation window. To mitigate the potential distortion caused by the exclusion of too many overlap-events, a shorter estimation window of 120 days was adopted instead of the 250 days introduced in MacKinlay (1997).

In the event study, we assume that the efficient market hypothesis (EMH) holds. Therefore, the error term must be zero since the return cannot systematically deviate from the expected return. Thus, the market model becomes:

$$R_{it} = \alpha_i + \beta_i R_{m_t} \tag{2}$$

The R_{it} is the expected return of stock *i* at time *t*. The α_i is the intercept term alpha, which is the constant term of the equation. The alpha represents the excess return of security *i* that is not explained by the security's sensitivity to the market that is represented by the beta coefficient β_i. The R_{m_t} is the market return that in this research is represented by the CRSP's value-weighted index return on time t. Following the market model equation, the abnormal return to be estimated is:

$$AR_{it} = R_{it} - \hat{\alpha} - \hat{\beta}_i R_{mt} \tag{3}$$

Where the AR_{it} is the difference between the observed return R_{it} minus the expected return $\hat{\alpha} + \hat{\beta}_i R_{mt}$.

The market-adjusted model is the second model employed. Following MacKinlay (1997), we use this model to cross-check the results obtained with the market model. This model assumes that predicted stock returns are the same between the securities but not necessarily constant for individual security. The market portfolio is a linear combination of all securities, and therefore the expected returns are E(Rit)=E(Rm)=K for any security *i* (Brown and Warner, 1980). The abnormal return measured after the divestiture announcement is the residual of the stock return *i* and market portfolio return,

$$AR_{it} = R_{it} - \bar{R}_{mt} \tag{4}$$

Where the R_{it} is the return of security *i* on day *t* minus the market or index return $\bar{R}_{mt}$.

Once ARs are calculated, we would like to aggregate the firm-specific ARs into average abnormal returns (AAR) at time t :

$$AAR_t = \frac{1}{N} \sum_{i=1}^{N} AR_{it} \tag{5}$$

Once the ARs and AARs are calculated, we are interested in the CARs that are the ARs cumulated over a certain event date period.

The CARs are computed by summing the ARs from the selected event window.

$$CAR_i(\tau_{1,}\tau_2) = \sum_{\tau=\tau_1}^{\tau_2} AR_{it} \tag{6}$$

Lastly, we calculate the cumulative average abnormal returns over the selected event windows of our sample by summing the AARs:

$$CAAR = \sum_{t=t1}^{t_2} AAR_t \tag{7}$$

As noted by De Jong (2007), the CAAR can also be calculated by averaging CARs in our sample:

$$CAAR = \frac{1}{N}\sum_{i=1}^{N} CAR_i \tag{8}$$

4.1.3 Testing the statistical significance of the CARs and CAARs

Conventionally t-test has been a popular choice to test the null hypothesis of zero means. While the conventional t-test is robust to event-induced volatility often present in stock price event studies, the test requires cross-sectionally independent events. This requirement is often not true, and we can observe that abnormal returns are not independent. Therefore, in this thesis, we will employ the standardized cross-sectional t-statistic that is robust to event-induced volatility (Boehmer et al., 1991). First, we standardize the $AR_{i,t}$ and $CAR_{i,t}$ values as:

$$SAR_{i,t} = \frac{AR_{i,t}}{\sqrt{Var(\varepsilon_{AR_i})}} \tag{9}$$

And,

$$SCAR_{i,t} = \frac{CAR_{i,t}}{\sqrt{N * Var(\varepsilon_{AR_i})}} \tag{10}$$

Where, ε_{AR_i} is the residual from the normal return model estimation for stock *i*, and *N* is the estimation window length.

Once the standardized version of ARs and CARs is calculated, we can compute the BMP or standardized cross-sectional (SCS) *t*-statistic:

$$t_{scs} = \frac{\frac{1}{M}\sum_{i=1}^{M} RV_{it}}{\sqrt{\frac{1}{M(M-1)}\sum_{i=1}^{M}\left[RV_i - \frac{1}{M}\sum_{i=1}^{M} RV_i\right]^2}} \tag{11}$$

Where,

RV= $SAR_{i,t}$or $SCAR_{i,t}$ and *M* is the number of announcements in the sample.

In conclusion, the standardization will dampen the effect of cross-sectional dependency, and the SCS *t*-statistic advised by Boehmer et al. (1991) is robust to event-induced volatility, which is in the favor regarding our stock returns data that often suffers from the issues mentioned above.

4.2 Cross-Sectional Regression Analysis

After obtaining the CARs, we are interested in testing possible drivers that affect CARs in our sample. The purpose of the regression is to test Hypothesis 2 and Hypothesis 3:

H2: Stronger financial performance of a divesting firm will lead to more positive CARs at the announcement.

and,

H3: Large divestiture size has a positive relationship with CARs at the announcement

The regression is run the $CAR_{0,1}$ as the dependent variable and net profit margin (NP), sales to working capital (SWC), current ratio (CR), book to market (BM), large deal dummy, natural logarithm of the parent firms' market value (ln_MV), subsector and year dummies as regressor variables. The NP, SWC, and CR variables are included to account for the parent firm's financial performance and therefore included to test hypothesis 2. The large deal dummy is included to test hypothesis 3, where we are interested in the coefficient's significance and magnitude. The MV is included to control for the firm size and subsector, and year dummies control for sector differences and year effects.

The general form of the model is:

$$CAR_{0,1} = \hat{\alpha}_0 + \hat{\beta}_1 NPM + \hat{\beta}_2 SWC + \hat{\beta}_3 CR + \hat{\beta}_4 BM + \hat{\beta}_5 LargeDealDummy + \hat{\beta}_6 \ln(MV) + \hat{\beta}_7 SubsectorDummy + \hat{\beta}_8 YearDummy + \varepsilon \tag{12}$$

We winsorized the dependent variable, net profit margin, and sales to working capital variables with 1% and 99% cut-offs to transform the distribution to follow a more normal form and mitigate the effect of outliers.

Additionally, since we assume that the error term's variance is constant in OLS, we test the heteroskedasticity with the Breusch-Pagan test to test the presence of heteroskedasticity. This is done by running the OLS and then squaring and rescaling the residuals so their mean equals one. After this, the reformulated residuals are regressed on the dependent variable. The test statistic is equal to the sum of squares divided by two (Berry & Feldman, 1985). The null of the test is that the error variances are homoscedastic, and the alternative is the presence of heteroskedasticity. We obtain a Chi-square value of 48.24 which is significant at the 1% level, indicating a strong presence of heteroskedasticity.

While heteroskedasticity does not affect OLS parameter estimates, it will affect standard errors, and so the t-values, making the statistical inference unreliable. Therefore, we run the OLS with robust standard errors that correct the non-constant variance in the error terms and produce more reliable *t*-statistics. Robust standard errors also account for the non-normality of the error term in the model. Q-Q plots of the residuals are found in Figure B.1 for the market model CAR regression, and market-adjusted CAR regression Q-Q plots of residuals are found in Figure B.2 (Appendix B). The Q-Q plots suggest that the error term is non-normal and, therefore robust standard error approach is justified.

We also check for the multicollinearity problem by inspecting the Pearson correlation table in Stata and then calculating variance inflation factors (VIFs) shown in Table 7. We observe low VIFs across the regressors while the mean VIF stays at 1.54 with the market model specification and 1.49 with the market-adjusted specification, indicating the absence of a multicollinearity problem.

Table 7: VIFs and Tolerances

Market model OLS	VIF	Market adjusted OLS	VIF
Ln_MV	2.42	Ln_MV	2.39
BM	1.56	BM	1.52
Large_deal	1.53	Large_deal	1.39
SWC	1.26	Netprofitmargin	1.23
Netprofitmargin	1.25	SWC	1.21
CurrentRatio	1.21	CurrentRatio	1.20
Mean VIF	1.54	Mean VIF	1.49

4.3 Pairwise Comparisons

While we do calculate the CAARs for individual subgroups, we are also interested in testing the differences with the Kruskal-Wallis test (Kruskal & Wallis, 1952) and running post-hoc with the Dunn's test (Dunn, 1964) to inspect multiple pairwise comparisons and their significance. The hypothesis under scrutiny here is hypothesis 4:

H_4 = The behavior of abnormal returns significantly varies across different subsectors

The Kruskal-Wallis test is a non-parametric method that relies on rank values. Utilization of ranks means that the test does not rely on normal distribution assumption. The test compares the medians of two or more groups. First, the values from all groups are combined, and ranks are assigned in order of smallest to largest values. For example, the smallest value gets a rank of one, and the second one gets a rank of two, and so forth. After the values are indexed with the ranks, the ranks are summed within each group. The test statistic is obtained as follows:

$$H = (N-1)\frac{\sum_{i=1}^{g} n_1 (\bar{r}_i - \bar{r})^2}{\sum_{i=1}^{g} \sum_{j}^{n_i} (\bar{r}_{ij} - \bar{r})^2} \qquad 13$$

Where N is the total number of observations across the groups, g is the number of groups, n_1 is the number of observations in group i, $\bar{r}_{ij}$ is the rank of observation from j from group i, $\bar{r}_i$ is the average rank of observation j from group i. $\bar{r}$ is the average of all the $\bar{r}_{ij}$.

The test statistic is then compared to the critical values that follow an approximately chi-squared distribution with g-1 degrees of freedom. The null hypothesis for the Kruskal-Wallis test is that the medians of the groups are equal. If the H statistic is larger than the corresponding critical value, the null is rejected, and at least one of the differences between groups differs significantly (Kruskal & Wallis, 1952).

Since the Kruskal-Wallis test does not say which of the difference or differences is significant, we run post-hoc testing with the Dunn test. The test extends to the Mann-Whitney U test and aims to control the type 1 error, which is often inflated with multiple comparisons. The null hypothesis for Dunn's test is that the medians of the two groups are equal. Dunntest calculates z-statistic for each pairwise comparison and then adjusts the p-values to account for the multiple comparison problem.

For Dunn's test, we have multiple methods to adjust the p-values of the results to mitigate the Type 1 error with multiple comparisons. We choose to use Sidak adjustment, where the familywise error rate (FWER) is adjusted by replacing the p-value of each pairwise comparison with $1-(1-p)^m$, where m is the number of pairwise tests (Sidak, 1967).

Chapter 5 Results

First, the results regarding the overall sample are presented. We use the -60 to +60-day period to calculate the day-specific ARs to check the general behavior of abnormal returns around the announcement date. We present the results graphically in Figure 2, with the CAARs, and numerically in Table 9. Then we calculate the CARs for the chosen event windows for the aggregate sample. We have two pre-event windows to check for information leakage, two event windows around the announcement date, and two post-announcement event windows to test hypothesis 5 of the persistence of abnormal returns. After the aggregate sample is analyzed, we divide the aggregate sample into large- and small divestitures defined by the 10% cutoff of the parent firm's market value. Then we separate the aggregate sample into the subsectors, calculate the abnormal returns, and conduct pairwise comparisons. Lastly, we introduce the results from regression model specifications.

5.1 Aggregate Sample

To address hypothesis 1: High technology divestiture announcement leads to positive abnormal returns on the share price of the divesting firm. The first point of interest is the CARs at the event date. Figure 3 visually shows how the abnormal returns behave around the event date. An apparent spike takes place on the event date and the day after. Also, a slight increase in the ARs was visible before the announcement. However, these increased ARs remained statistically insignificant in our sample, as shown in Table 8 beside day -9, which most likely results from general noise in the data. The differences in CAARs between the two models are negligible, and the two-sample *t*-test failed to reject the hypothesis of equal means between the two models with a two-tail p-value of 0.763.

Figure 3 visualizes the behavior of ARs and CAARs over the long -60 to +60 event window. We can see a strong increase in abnormal returns on the event date. Beyond the event date, the ARs seem to fluctuate randomly, but the post-announcement CAARs included in Table 9 are statistically insignificant.

Figure 3: ARs and CAARs Over -60 to +60 Event Window

Note. The expected return is calculated with a market model employing 314 valid return calculations from the sample that excludes overlapping events during the estimation period.

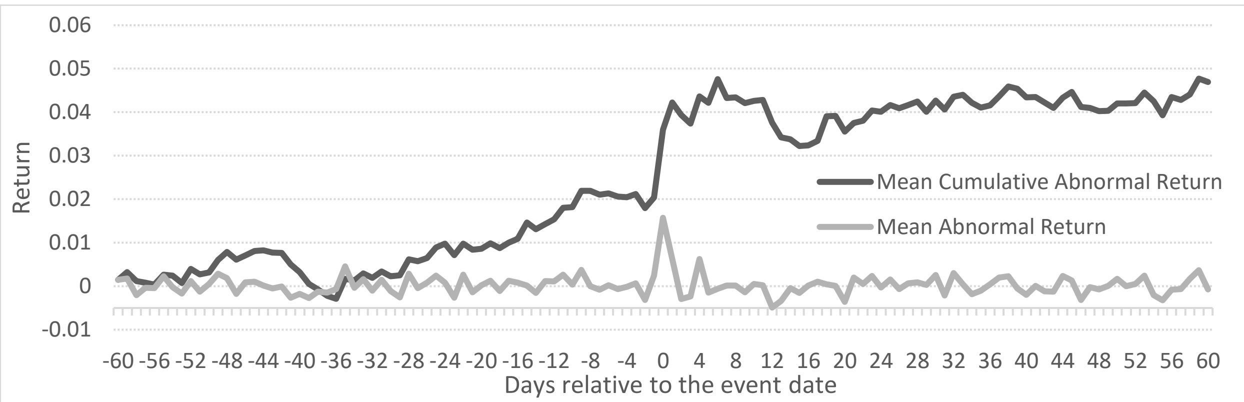


Table 8 provides a numerical representation of the AARs and includes the BMP *t*-statistics with both normal return models used. We can observe that event date 0 is significant at the 1% level, but the following day is only significant with the market-adjusted model. The reason for the difference remains ambiguous, but the *p*-value of 0.1376 for the market model's day two provides some indication beyond the conventional levels. These findings indicate that the wealth effect is present in our sample at the announcement and on the following day to some degree. This finding supports the decision to focus on the two-day event window ($CAR_{0,1}$) as our main interest.

The results do not exhibit significant information leakage for individual AARs before the announcement event besides day -9, which is statistically significant. This finding contradicts the findings of Afshar et al. (1991), who found significant abnormal returns on day -1 due to the information leakage before the press announcement of divestitures. However, we get a strong visual hint in Figure 3 regarding the behavior of the $CAAR_{-60,60}$, which increases around 35 days before the announcement date. That increase in slope gives us a reason to include an event window of -35 to -1 in our event window catalog to check for information leakage that might cause this phenomenon. In addition, for caution, we also implement a shorter pre-event window of -3 to -1 days. Other than that, AARs seem to fluctuate randomly around the announcement. The difference column reports the differences between AARs obtained with a two-model approach. While we do not directly test the difference with statistical methods, we can state that the differences are minor and indicate the robustness of the two model approach despite the disparity in the sample sizes due omittance of overlapping observations in the market model estimations.

Table 8: Average Abnormal Returns of Aggregate Sample

Note. This table reports ARs calculated with market and market-adjusted models and their BMP *t*-values. The last column reports differences between ARs, and the differences were tested with a *t*-test assuming equal variance. The *t*-values are from a standardized test that is robust to cross-sectional dependence and event-induced variance. The market model has 314 observations, and market adjusted 349. The differences in the aggregate sample size are due to missing returns during the estimation period that have caused some of the observations to be omitted from the estimations.

Day	AAR Market model	*t*	AAR Market adjusted	*t*	Difference
-60	0.0015	-0.0114	0.0006	0.2175	0.001
-50	0.0002	0.8287	0	0.6898	0.0002
-40	-0.002	-0.9783	-0.0015	-0.8798	-0.0005
-30	-0.0009	0.3611	-0.0007	0.814	-0.0002
-20	-0.0001	0.3216	0.0004	0.3105	-0.0005
-10	0.0002	-0.0859	-0.0003	-0.4358	0.0005
-9	0.004	1.3051	0.0042	2.0015**	-0.0002
-8	0	0.0553	-0.0007	-0.3973	0.0007
-7	-0.001	-1.1277	-0.0017	-1.4216	0.0007
-6	0.0002	0.4208	-0.0013	-0.3055	0.0015
-5	-0.0006	-1.0282	0.0003	-0.0993	-0.0009
-4	-0.0003	0.0667	-0.0005	0.1229	0.0001
-3	0.0003	0.9439	-0.0009	-0.0119	0.0013
-2	-0.0032	-1.4313	-0.0007	-0.3697	-0.0025
-1	0.0021	0.6594	0.0031	1.1668	-0.001
0	0.0158	3.2291***	0.0107	3.3499***	0.0051
1	0.0057	1.5188	0.0075	2.424**	-0.0018
2	-0.0027	-0.1564	0.0016	0.7177	-0.0043
3	-0.0025	-0.8645	-0.0021	-0.5451	-0.0004
4	0.0062	1.2185	0.0054	1.4189	0.0009
5	-0.0015	-0.5181	-0.0003	0.8857	-0.0011
6	-0.0006	-0.0408	0.0004	0.5907	-0.001
7	0.0001	-0.1846	-0.0015	-0.7695	0.0016
8	0.0001	-0.8013	-0.0005	-0.6301	0.0006
9	-0.0013	-0.0727	-0.0009	0.0768	-0.0004
10	0.0002	-0.0568	0.0001	-0.4647	0.0001
20	-0.0039	-1.7915*	-0.0039**	-2.462	0
30	0.0025	0.8656	0.0021	0.6826	0.0004
40	-0.0021	-0.9147	-0.0011	-0.3133	-0.001
50	0.0013	0.0541	0.002	0.4503	-0.0007
60	-0.0005	-0.4687	-0.0015	-1.1992	0.001

*** *p<0.01, ***p<0.05, *p<0.1*

Table 9 reports CAARs calculated for various intervals of interest. The CAARs calculated with the two models produce similar results despite the small difference in the sample size. The pre-announcement event windows $CAAR_{-35,-1}$ and $CAAR_{-3,-1}$ are insignificant and close to zero and therefore do not indicate information leakage. All the event windows $CAAR_{0,1}$ and $CAAR_{-3,3}$ over the announcement day are positive and significant. The post-announcement windows $CAAR_{2,10}$ and $CAAR_{11,60}$ stay insignificant and therefore do not present evidence against hypothesis 5 regarding the absence of post-event abnormal return persistence.

Table 9: CAARs of the Aggregate Sample

Model	Interval t1-t2	N	$CAAR_{t1,t2}$	*t*
Market model	-35 to -1	322	0.0093	1.3187
	-3 to -1	320	-0.0001	0.4223
	0 to +1	318	0.0198***	3.5047
	-3 to +3	319	0.0139**	2.5360
	+2 to +10	318	0.0005	0.0113
	+11 to +60	312	-0.0144	-0.9700
Market adjusted	-35 to -1	356	0.0075	1.0881
	-3 to -1	353	0.0018	1.2062
	0 to +1	352	0.0180***	4.1111
	-3 to +3	353	0.0191***	3.9065
	+2 to +10	351	0.0034	0.7159
	+11 to +60	345	-0.0137	-1.2621

**** p<0.01, ***p<0.05, *p<0.1*

The results obtained with the aggregate high-technology sample provide strong evidence in favor of hypothesis 1 that divestitures lead to a positive wealth effect for the parent firm's shareholders. We do not observe information leakage before the event. The post-announcement CAARs are small and statistically insignificant. This finding implies the non-persistence of abnormal returns, meaning that the efficient market hypothesis holds at least in its semistrong form.

Once we have concluded the presence of positive wealth effects at the aggregate sample level, we continue to study the divestiture's size effect on the announcement returns. The following sections, through 5.2 to 5.5, will test the hypotheses related to the different factors potentially affecting abnormal returns. We are beginning with the deal size effect, advancing with inspection of the subsectors inside the aggregate sample, and ending up with the regression analysis in part 5.5, where factors in our hypotheses are put against the two-day $CAR_{0,1}$.

5.2 Deal Size Effect

The deal size effect is calculated to test hypothesis 3: the size of divestiture has a positive relationship with CARs at the announcement. We first split the aggregate sample into two subsamples; 'small' and 'large.'

If the deal value is less than or equal to 10% of the firm's market value, divestiture is defined as small, and if larger than 10%, then the divestiture is considered large. The same event windows are used as in part 5.2 despite the excluded post-announcement periods. The CAARs are calculated using the same two-model approach to cross-validate the results.

In the small divestitures subsample, the CAARs calculated with the market model remain consistently close to zero and statistically insignificant at all conventional levels. The market-adjusted approach provides similar results despite the pre-event $CAAR_{-35,-1}$, which is significant at the 10% level. The insignificance of CAARs in the small subsample is insightful because the small divestitures are a big part of the aggregate sample by the 205 announcements compared to the 142 announcements in the large subsample. We can justify that the small divestitures in our aggregate sample pull down the CAARs in Table 9. Also, due to small deal sizes, subsectors such as "Other high technology" and Internet Software and Services might remain insignificant.

Table 10: CAARs of Small Divestitures

Model	Interval t1-t2	N	$CAAR_{t1,t2}$	*t*
Market model	-35 to -1	187	0.0155	1.6235
	-3 to -1	187	0.0046	1.3065
	0 to +1	186	0.0022	0.3756
	-3 to +3	187	0.0028	0.8236
	+2 to +10	186	-0.0101	-1.1600
	+11 to +60	186	-0.0295	-0.8609
Market adjusted	-35 to -1	205	0.0170*	1.89336
	-3 to -1	205	0.0058	1.6251
	0 to +1	204	0.0029	0.7669
	-3 to +3	205	0.0055	1.3656
	+2 to +10	204	-0.0073	-0.7570
	+11 to +60	202	-0.0184	-0.7822

*** *p<0.01, ***p<0.05, *p<0.1*

In the large divestitures subsample, we found strong announcement effects. The pre-event period stays close to zero with both models and is statistically insignificant. The immediate two-day CAARs with both models are positive and significant at a 1% level. The following $CAAR_{-3,3}$ is also positive and inhibits strong statistical significance at the 1% level. According to this evidence, we fail to reject hypothesis 3 and conclude that larger divestitures will lead to more positive CAARs, at least around the event date, and these are seen as value-adding transactions. We include the large deal size dummy in the OLS regression to closely inspect the magnitude and significance of the difference between the two groups. The important finding is that post-announcement persistence exists in the subsample of large divestitures. We observe significant post-event $CAAR_{2,10}$ values with both approaches. This persistence of post-announcement persistence indicates a violation of the semi-strong form efficient market hypothesis where the new information should be reflected in the equity prices immediately and leads to partial rejection of hypothesis 5 regarding no post-announcement existence in high-technology divestitures.

Table 11: CAARs of Large Divestitures

Model	Interval t1-t2	N	$CAAR_{t1,t2}$	*t*
Market model	-35 to -1	136	0.0082	0.3045
	-3 to -1	135	-0.0019	-0.3233
	0 to +1	135	0.0405***	4.2790
	-3 to +3	135	0.0433***	3.8166
	+2 to +10	134	0.0303***	1.9949
	+11 to +60	130	0.0344	0.2852
Market adjusted	-35 to -1	144	-0.0059	-0.5260
	-3 to -1	142	-0.0029	-0.1398
	0 to +1	142	0.0405***	4.3541
	-3 to +3	142	0.0408***	3.8902
	+2 to +10	141	0.0211**	1.7532
	+11 to +60	137	-0.0013	-0.769

**** p<0.01, ***p<0.05, *p<0.1*

5.3 Subsector CAARs

This part of the chapter distinguishes the subsectors from the aggregate high-technology sample and represents the CAAR calculations for selected event windows. We calculate the results to test hypothesis 1 and produce the two-day $CAAR_{0,1}$ estimations to test hypothesis 4 if the announcement returns differ significantly between the different subsectors in part 5.4, where we calculate and present pairwise comparisons across the different subsamples. The post-announcement event windows are included to test hypothesis 5 regarding the possible post-announcement persistence of abnormal returns.

5.3.1 Computers and Peripherals

Table 12 shows the CAARs calculated with the market model and market-adjusted model. The market model does not indicate information leakage. The immediate two-day $CAAR_{0,1}$ estimations are all significant at the conventional levels. The market model's seven-day $CAAR_{-3,3}$ is significant at the 10% level, while the market-adjusted $CAAR_{-3,3}$ remains insignificant. We also do not see an indication of post-announcement persistence abnormal return since the $CAAR_{2,10}$ and $CAAR_{11,60}$ stay insignificant.

Therefore, we can conclude that the computers and peripherals subsample is consistent with the positive divestiture announcement returns consensus and does not suffer from pre- and post-announcement complications.

Table 12: CAARs of Computers and Peripherals Subsample

Model	Interval t1-t2	N	$CAAR_{t1,t2}$	*t*
Market model	-35 to -1	53	-0.0022	-0.0517
	-3 to -1	54	0.0021	0.6775
	0 to +1	54	0.0199**	2.3917
	-3 to +3	54	0.0278*	1.9987
	+2 to +10	54	0.0154	1.0765
	+11 to +60	51	-0.0125	0.0606
Market adjusted	-35 to -1	58	0.0007	-0.5921
	-3 to -1	59	-0.0029	-0.1592
	0 to +1	59	0.0197**	2.3080
	-3 to +3	59	0.0199	1.6594
	+2 to +10	59	0.0161	1.4072
	+11 to +60	56	-0.0094	0.1790

***** *p<0.01, ***p<0.05, *p<0.1*

5.3.2 E-Commerce B2B

The pre-event interval indicates an absence of information leakage. The immediate two-day $CAR_{0,1}$ is significant with both models and stays significant on the wider event windows around the announcement. We can conclude that despite the relatively small sample size in the space of E-commerce, we have strong evidence supporting hypothesis 1 of positive wealth effects for the parent firms' shareholders. We also do not see abnormal returns persistence, which supports hypothesis 5.

Table 13: CAARs of E-Commerce B2B Subsample

Model	Interval t1-t2	N	$CAAR_{t1,t2}$	*t*
Market model	-35 to -1	20	0.0101	0.4405
	-3 to -1	20	-0.0044	0.1788
	0 to +1	20	0.0364**	2.6165
	-3 to +3	20	0.0274**	2.1115
	+2 to +10	20	0.0137	0.6935
	+11 to +60	20	-0.0443	-0.4842
Market adjusted	-35 to -1	22	0.0085	0.9883
	-3 to -1	22	-0.0022	0.5050
	0 to +1	22	0.0336**	2.6726
	-3 to +3	22	0.0289**	2.5858
	+2 to +10	22	0.0138	1.0547
	+11 to +60	22	-0.0461	-0.2400

**** p<0.01, ***p<0.05, *p<0.1*

5.3.3 Electronics

The electronics subsector's CAARs are positive but remain statistically insignificant across the two models and the chosen event window intervals. The possible reasons why the CAARs are insignificant can be complex and out of the scope of this paper. However, 43.59% of the 39 announcements are large and represent a minority share in the aggregate subsample. This share of small divestments in the sample could mitigate the statistical significance of CAARs, as demonstrated in Chapter 5.3, where we found that, on average, relatively small divestitures remain insignificant at the conventional levels with our aggregate high-tech sample.

Despite the positive $CAAR_{0,1}$ estimations that are closer to the conventional significance levels than other intervals in the subsample, we must state that we do not observe enough statistical evidence to conclude significant results supporting hypothesis 1 about positive divestiture announcement returns in the electronics subsample.

Table 14: CAARs of Electronics Subsample

Model	Interval t1-t2	N	$CAAR_{t1,t2}$	*t*
Market model	-35 to -1	37	-0.0262	-0.8665
	-3 to -1	36	0.021	0.4985
	0 to +1	36	0.0312	1.553
	-3 to +3	36	0.0342	0.7183
	+2 to +10	36	0.0090	0.5834
	+11 to +60	36	0.0240	0.7608
Market adjusted	-35 to -1	39	-0.0516	-0.7884
	-3 to -1	38	0.0181	0.5078
	0 to +1	38	0.0295	1.3390
	-3 to +3	38	0.0294	0.6798
	+2 to +10	38	0.0019	0.0632
	+11 to +60	38	0.0036	0.1017

**** p<0.01, ***p<0.05, *p<0.1*

5.3.4 Internet Software and Services

Information leakage is not visible before the internet software and services category announcement. The immediate announcement effect is negative by 3.53% and statistically significant by the market model estimation, which is against the consensus and hypothesis 1 for announcement effects, and the $CAAR_{0,1}$ with the market-adjusted return is negative and insignificant with a *p*-value of 0.2105. The subsample does not indicate abnormal returns persistence which supports Hypothesis 5.

The remaining results remain negative and insignificant despite the seven-day window measured with the market model. Due to the financial theory, we should assume that the market model measures normal performance more accurately. Therefore it could be argued that the negative CAARs take place with great certainty even when the market-adjusted approach does not entirely support that finding.

These results suggest that there exist industries where divestitures are not necessarily beneficial for the parent firm's shareholders. This finding would also suggest future research to study the internet software and services sector more in detail to clarify the reasons behind negative announcement returns.

Table 15: CAARs of Internet Software and Services Subsample

Model	Interval t1-t2	N	$CAAR_{t1,t2}$	*t*
Market model	-35 to -1	31	0.0017	0.7410
	-3 to -1	30	0.0032	0.6244
	0 to +1	30	-0.0353**	-2.3940
	-3 to +3	30	-0.0278*	-1.7449
	+2 to +10	30	-0.0027	0.2797
	+11 to +60	28	-0.0640	-1.0991
Market adjusted	-35 to -1	34	-0.0245	0.4263
	-3 to -1	32	0.0030	0.6203
	0 to +1	32	-0.0255	-1.2786
	-3 to +3	32	-0.0184	-0.8659
	+2 to +10	32	0.0089	0.8380
	+11 to +60	30	-0.0567	-0.8600

**** p<0.01, ***p<0.05, *p<0.1*

5.3.5 IT Consulting and Services

Table 16 reports abnormal return calculations for IT Consulting and Services subsample. This subsample does not indicate information leakage before the announcement, but it should be noted that the *t*-statistics indicate an approach toward the conventional significance levels. The two-day $CAAR_{0,1}$ is positive and significant at the 5% level with the market model. The seven-day $CAAR_{-3,3}$ is also positive and significant at the 10% level.

We should note that market model $CAAR_{11,60}$ is almost significant at the 10% level and negative. That effect is also visible with the market-adjusted approach, where the same $CAAR_{11,60}$ is negative and significant at the 10% level. Therefore, we observe a significant post-announcement drift, but, in this case, it happens to the opposite side of what was expected in hypothesis 5.

Table 16: CAARs of IT Consulting and Services Subsample

Model	Interval t1-t2	N	$CAAR_{t1,t2}$	*t*
Market model	-35 to -1	48	0.0009	1.4072
	-3 to -1	47	-0.0054	-1.6638
	0 to +1	47	0.0443***	2.7615
	-3 to +3	47	0.0298	1.6294
	+2 to +10	47	0.0180	0.5494
	+11 to +60	47	-0.0465	-1.4994
Market adjusted	-35 to -1	56	0.0025	1.3092
	-3 to -1	55	-0.0003	-0.0666
	0 to +1	55	0.0510***	3.1764
	-3 to +3	55	0.0453***	2.7426
	+2 to +10	55	0.0111	0.5886
	+11 to +60	55	-0.0599*	-1.6862

**** p<0.01, ***p<0.05, *p<0.1*

5.3.6 Semiconductors

The semiconductors subsample does exhibit signs of information leakage. Both models indicate positive abnormal returns during the -35 to -1 and -3 to -1 days intervals. This finding raises a question regarding how much the pre-event leakage mitigates the abnormal returns at the event date. The two-day $CAAR_{0,1}$ estimations are significant with both model approaches at the 10% level, which is less significant than found in the other subsamples with positive and significant announcement effects. We do not observe evidence for post-announcement drift in abnormal returns.

Table 17: CAARs of Semiconductors subsample

Model	Interval t1-t2	N	$CAAR_{t1,t2}$	*t*
Market model	-35 to -1	75	0.0620*	1.7686
	-3 to -1	75	0.0074*	1.6768
	0 to +1	75	0.015*	1.8056
	-3 to +3	75	0.0215*	1.9587
	+2 to +10	75	-0.0112	-1.0097
	+11 to +60	74	-0.0198	-1.2395
Market adjusted	-35 to -1	82	0.0699***	3.0742
	-3 to -1	82	0.0078**	2.0952
	0 to +1	82	0.0146*	1.9637
	-3 to +3	82	0.0213**	2.2406
	+2 to +10	82	-0.0195	-1.1549
	+11 to +60	81	-0.0252	-1.2080

**** p<0.01, ***p<0.05, *p<0.1*

5.3.7 Software

With software subsample, all the CAARs remain insignificant. Two-day CAARs are positive but stay insignificant with our sample despite an approach toward significance. We state that software divestitures do not yield significant abnormal returns despite the decent sample size. This finding would require further research to study why this is the case in the software divestitures subsample.

Table 18: CAARs of Software subsample

Model	Interval t1-t2	N	$CAAR_{t1,t2}$	*t*
Market model	-35 to -1	51	-0.0125	-0.5555
	-3 to -1	51	-0.0107	-0.2649
	0 to +1	50	0.0223	1.4563
	-3 to +3	51	0.0081	1.1924
	+2 to +10	50	0.0007	0.4914
	+11 to +60	50	0.0543	0.5327
Market adjusted	-35 to -1	54	0.0143	1.0471
	-3 to -1	54	-0.0107	-0.5143
	0 to +1	53	0.0195	1.2178
	-3 to +3	54	0.0038	0.7651
	+2 to +10	53	0.0022	0.2206
	+11 to +60	53	0.0306	0.2361

**** p<0.01, ***p<0.05, *p<0.1*

5.3.8 Other High Technology

The other high-tech subsample suffers from a low sample size. As expected, the results are inconsistent. However, we observe significant pre-event $CAAR_{-35,-1}$ with the market-adjusted model, while the market model counterpart approaches significance.

Table 19: CAARs of Other High-Technology Subsample

Model	Interval t1-t2	N	$CAAR_{t1,t2}$	*t*
Market model	-35 to -1	8	0.1018	1.7151
	-3 to -1	8	-0.0002	0.7
	0 to +1	8	0.0045	0.3486
	-3 to +3	8	-0.0028	0.9576
	+2 to +10	8	-0.0222	-1.3587
	+11 to +60	8	0.0592	0.7373
Market adjusted	-35 to -1	10	0.0840**	2.4757
	-3 to -1	10	0.0082	1.7724
	0 to +1	10	0.0152	1.5623
	-3 to +3	10	0.0126	1.7130
	+2 to +10	10	-0.0175	-0.7558
	+11 to +60	10	0.0202	0.4730

**** p<0.01, ***p<0.05, *p<0.1*

5.4 Pairwise Comparisons of Subsector CARs

We run the Kruskal-Wallis test to statistically test hypothesis 4 that there is a difference in announcement returns between the different subsectors. If the test indicates statistical significance, we run Dunn's pairwise comparison to observe which group or group differs and the properties of the difference.

The results of Kruskal-Wallis and Dunn's tests are reported for market model two-day $CAR_{0,1}$ in Table 20. The variable of interest used in the tests is the two-day market model $CAR_{0,1}$. Table 20 represents the different subsectors, the respective amount of observations, rank sums, and the chi-square test statistic. The test statistic has a *p*-value of .0424. Therefore, we can reject the null hypothesis of equal medians between the groups and continue with Dunn's test pairwise comparison of the subsectors.

Table 20: Kruskal-Wallis Test With Market Model $CAR_{0,1}$ Estimation

Note. The test statistic indicates significance at the 5% level.

Subsector	Index	N	Rank sum
Computer & Peripherals	1	54	8612.00
E-Commerce & B2B	2	20	3671.00
Electronics	3	36	5846.00
Internet & Software Services	4	30	3135.00
IT Consulting & Services	5	47	8300.00
Other High-Technology	6	8	1181.00
Semiconductors	7	75	12698.00
Software	8	50	7917.00
Chi-square		14.538	
		(.0424)	

In Table 21, we report the results of Dunn's pairwise comparison. The differences are widely insignificant, but group 4, Internet Software & Services, has significant differences. First, the difference between E-commerce & B2B (2) and Internet & Software Services (4) is positive and significant at the 5% level. Implying that the E-commerce & B2B subsector has significantly higher abnormal returns at the announcement, measured with two-day $CAAR_{0,1}$.

The second statistically significant difference is between Internet & Software Services (4) and IT Consulting & Services(5). The negative result implies that the Internet & Software Services (4) subsector tends to have significantly lower abnormal returns than IT Consulting & Services at the announcement.

The third significant difference is between Internet & Software Services (4) and Semiconductors (7). The result indicates that Internet & Software Services (4) have significantly lower abnormal returns at the announcement than the Semiconductors (7). We used conservative Sidak adjustment of the *p*-values, meaning we tried to minimize the chance of Type 1 error. Despite being insignificant, we could still see that all other results for Internet & Software Services (4) indicate lower $CAAR_{0,1}$. At this point, we should remind ourselves that Internet & Software Services were a subsector that was found to have negative CAARs. This finding suggests further research done in the subsector to conclude why this subsector suffers from significantly lower announcement returns compared to what we expect according to the consensus of positive wealth effects of divestitures.

Table 21: Dunn's Pairwise Comparison of $CAR_{0,1}$ by Subsectors

Col - Row	1	2	3	4	5	6	7
2	-0.9938						
	(0.993)						
3	-0.1460	0.8201					
	(1.000)	(0.9984)					
4	2.6097	2.9598**	2.5310				
	(0.119)	(0.042)	(0.148)				
5	-0.9272	0.2815	-0.6933	-3.3345**			
	(0.996)	(1.000)	(0.999)	(0.012)			
6	0.3383	0.9281	0.4083	-1.1714	0.8187		
	(1.000)	(0.996)	(1.000)	(0.973)	(0.998)		
7	-0.5950	0.6117	-0.3688	-3.2425**	0.4235	-0.6301	
	(1.000)	(1.000)	(1.000)	(.017)	(1.000)	(1.000)	
8	0.0629	1.030	0.2002	-2.5198	0.9712	-0.3041	0.649
	(1.000)	(0.990)	(1.000)	(0.152)	(0.994)	(1.000)	(1.000)

**** p<0.01, ***p<0.05, *p<0.1*

5.5 Regression Analysis

The multivariate analysis with robust standard errors is done to test the relationship between different hypothesized drivers of abnormal returns. Hypothesis 2 about the positive relationship between announcement returns and a firm's financial performance is tested by including net profit margin, book-to-market, sales to working capital, and current ratio. Hypothesis 3 regarding the possible positive effect of large divestiture on the announcement returns is studied by including the large deal size dummy variable. We also include the firms' market value to control the firms' size.

The analysis is run first against the market model's $CAR_{0,1}$ (1A and 1B) and then with the market-adjusted model's $CAR_{0,1}$ (2A and 2B) for robustness. As described above, we include the deal size dummy to inspect the difference and its significance between the small- and large divestitures subsample. The year- and subsector dummies are included to control differences in year-to-year and subgroup effects. We also run another regression without the year – and subsample controls for comparison (1B and 2B).

Table 22 presents the OLS estimations done with the market model's (1AB) and market-adjusted model's (2AB) two-day CARs. First, all models behave similarly despite the difference in the sample sizes. All models are significant at the 1% level measured by the *F*-statistic. The R-squared and adjusted R-squared metrics are included and indicate that, at best, our model explains 16.36% of the variability in specification 2A. Otherwise, the differences between the fit measures are negligible across the specifications.

Starting from the net profit margin variable's coefficient, we have a significant estimation at the 1% level. Also, the different models' positive magnitude is close to each other. This positive coefficient supports hypothesis 2, that financial performance positively correlates with announcement returns, and high-performing firms act proactively and aim to further increase their efficiency rather than being forced and making the divestment decision reactively.

Sales to working capital was another financial performance and efficiency metric. With 1A, 2A, and 2B, it stays above the 10% level but turns significant with model 1B, where the subsector and year controls are relaxed. The coefficient is negative, close to zero, and significant only in model specification 1B with a small negative effect. However, we argue that all else equal, we have some proof that sales to working capital potentially affect the announcement returns despite its slight insignificance.

The current ratio is the third financial performance regressor. Its coefficient is negative and significant with all the model specifications despite specification 1A. In economic terms, a firm already holding a high amount of liquid assets could suffer from the opportunity cost of capital, where it cannot utilize its short-term assets efficiently. A divestiture could make this problem more severe when the company receives the proceeds from the transaction — concluding that holding a high level of liquidity is not always a sign of a healthy business, which is reflected in the announcement returns of divestment.

Book to market is a metric of a firm's valuation. The estimated coefficient is aligned with the economic interpretation that divestiture announcement of value firms with a high book-to-market ratio could be seen as a strategic refocusing, where inefficient parts of the business are sold. The market could interpret that divestiture as a strategic move to improve the firm's prospects, which is reflected in the positive announcement returns.

Additional assessment concerns the interpretation that book-to-market ratios can be a proxy for intangible asset value, as Peters & Taylor (2014) argued. The value of high-tech firms and, therefore, the acquisition price depends on intangible assets. This dependency would lead to a pronounced announcement return in the divestiture where the value of intangible assets is recorded as goodwill and materializes in the transaction price. The coefficient indicates that the book-to-market effect is present. All else equal, firms with a high BM ratio will experience a larger announcement effect. However, a closer inspection of the effect would require us to control the amount of goodwill present on the firm's balance sheet, allowing us to potentially estimate the amount of intangibility.

Lastly, the dummy for large deal value is positive and significant at the 5% level in 1A and the 1% level in 1B, 2A, and 2B. This positive coefficient complements the earlier analysis between the small- and large subsamples done in 5.2. We can conclude that all else equal, the large divestitures, on average, do yield to 3.71% (1A) or 3.59% (2A) larger effect than small divestitures when the firm's market value, year, and subsector controls are imposed.

Table 22: Multivariate OLS Results with Robust Standard Errors

Model specification 1 includes $CAR_{0,1}$ from market model estimation, and model specification 2 includes $CAR_{0,1}$ from market-adjusted model estimation as the dependent variable. The market value variable is the natural logarithm of the parent firm's market value at the time of divestiture announcement. Corresponding *p*-values are in parentheses.

Regressor	1A	1B	2A	2B
Net profit margin	0.0273***	0.0290***	0.2650***	0.0277***
	(.006)	(.009)	(.000)	(.001)
Sales to working	-0.0010	-0.0012**	-0.0007	-0.0007
capital	(.111)	(.016)	(.142)	(.118)
Current ratio	-0.0064	-0.0454**	-0.0058**	-0.090**
	(.108)	(.045)	(.025)	(.033)
Book to market	0.0337*	0.0374**	0.0311**	0.0297**
	(.051)	(.015)	(.048)	(.037)
Large deal dummy	0.0371**	0.0413***	0.0359***	0.0383***
	(.013)	(.006)	(.002)	(.001)
Market value	-0.0059*	-0.0033	-0.0061**	-0.0043*
	(.062)	(.229)	(.040)	(.098)
Subsector controls	Yes	No	Yes	No
Year controls	Yes	No	Yes	No
Constant	0.0733	0.0325	0.0587	0.4120
	(.203)	(.287)	(.241)	(.147)
R-squared	0.2486	0.1561	0.2367	0.1490
Adj. R-squared	0.1622	0.1328	0.1636	0.1292
F-statistic	2.25***	5.02***	2.74***	5.44***
	(.002)	(.000)	(.000)	(.000)
Observations	224	224	264	264

**** p<0.01, ***p<0.05, *p<0.1*

Chapter 6 Discussion

This thesis aims to answer the following research question:

To what extent do corporate divestments create value for the parental firms' shareholders in the US high technology sector?

We formulated five different hypotheses which aimed to provide answers to the research question. Following the event study methodology, we calculated abnormal and cumulative abnormal returns for the divestiture announcements. The market and market-adjusted models were used to calculate the normal returns, and the CRSP value-weighted index represented the market return in the estimation of the normal returns with the market model. The results were tested with a standardized t-test that is robust to cross-sectional correlation and event-induced variance.

First, multiple measures were computed with the aggregate high-technology sample to test hypothesis 1. Secondly, hypothesis 2, the relationship between the parent firms' financial performance and abnormal returns, was tested with regression analyses. Thirdly, hypothesis 3 regarding the relative deal size effect was tested by first dividing the divesting firms into small and large groups and calculating the CAARs and significances for the groups. In addition, for hypothesis 3, we included the deal size dummy in the regression models to inspect the deal size effect while other factors are taken into the equation. Then hypothesis 4 regarding differences in the abnormal returns among different sub-sectors in the US high technology sector was considered, first, by calculating the cumulative average abnormal returns for each subsector over selected event windows and then using pairwise comparison techniques to study the significance and direction of the differences. Then, auxiliary hypothesis 5 about abnormal returns persistency in the post-announcement period was tested by including the two post-announcement event windows into each step where abnormal returns were measured.

The following Table 23 reports the results for each of the hypotheses defined in this paper. In the case of subsample results contradicting aggregate sample results, we present the condition for accepted or rejected results with the superscript and provide elaboration of the contradiction in notes of Table 23.

Table 23: Results of Hypotheses

Note. [a]Internet Software & Services subsample indicated negative announcement returns measured by the two-day $CAAR_{0,1}$. [b]Large divestitures subsample indicates positive and significant post-announcement abnormal returns at +2 to +10 days event window. IT Consulting & Services subsample indicated evidence of negative post-announcement abnormal return persistence.

Order	Hypothesis	Result
1	A high-technology divestiture announcement leads to positive abnormal returns on the share price of the divesting firm.	Accepted[a]
2	A parent firm’s financial performance has a positive relationship with abnormal returns at the announcement.	Accepted
3	The size of the divestiture has a positive relationship with abnormal returns at the announcement.	Accepted
4	The behavior of abnormal returns significantly varies between different subsectors.	Accepted
5	The stock prices do not reflect significant post-announcement abnormal return persistence to the direction of the announcement effect.	Accepted[b]

For hypothesis 1, the day-specific AARs indicated statistical significance on day 0 and day 1, and therefore we found the two-day $CAAR_{0,1}$ positive and significant, supporting hypothesis 1. In the aggregate sample, the abnormal returns were not visible after the event window, which supports the efficient market hypothesis and accepts hypothesis 5.

However, in the subsample of large divestitures, we observed significant post-announcement abnormal returns during the +2 to +10 event window. This finding contradicts the findings of Fu & Huang (2016) regarding the disappearance of abnormal returns after corporate stock transactions. On the aggregate level, we did not observe the persistence of the abnormal returns, which justifies the power and usage of event study methodology and fails to reject hypothesis 5.

The regression analyses were done to study hypothesis 2. The key variables to observe the financial soundness and efficiency were the net profit margin, sales to working capital, current ratio, and book-to-market ratio (1A, 1B, 2A, and 2B).

We found that the net profit margin (NPM) is significant with all model specifications and indicated a positive relationship between the two-day $CAR_{0,1.}$ Sales to working capital (SWC) was negative and remained just outside the 10% level despite the market model specification 1B, where year- and sector controls were relaxed, where it turned significant at the 5% level. We still argue that the variable has explanatory power, and the keeping of the variable was justified, especially in the absence of a multicollinearity problem. SWC dictated a small but negative relationship with the CAR_{01}. The negative coefficient predicts that firms with less efficient operations benefit more from divestitures than more efficient ones. This fact is in line with the consensus.

The coefficient for the book-to-market variable was positive and significant with all the specifications, meaning that value firms benefit more from the divestitures than growth firms. This finding aligns with the book-to-market effect, where the value firms with high book-to-market ratios will earn positive excess returns while low book-to-market firms earn negative excess returns (Cakici & Topyan, 2014). Additionally, this finding follows an interpretation where value firms are possibly holding onto inefficient and aging assets in the dynamic high-technology industry. We suggest that future research would study the book-to-market value more closely by controlling the goodwill on the parent firm's balance sheet and investigating how the level of intangible assets affects the announcement returns of the divestiture transaction.

For hypothesis 3, we first divided the aggregate sample into 'small' and 'large' subsamples. While the CAARs in the small subsample remained insignificant, the large subsample exhibited strong significance. In addition, the large subsample indicated abnormal return persistence after the announcement measured by +2 to +10 event window, which is against hypothesis 5 and the findings of Fu & Huang (2016) regarding the disappearance of abnormal returns after corporate stock transactions.

We continued testing hypothesis 3 in the regression analysis, where we included the large deal size dummy in the regression equation. We found that the coefficients for large divestiture are strongly significant and positively affect the abnormal returns across the model specifications. By including the large deal dummy variable into the OLS equation, we found that all else equal, on average large deals lead to a 3.71% (Market Model) or 3.59% (Market adjusted) larger announcement effect than small divestitures when controlling year-and subsector effects.

For hypothesis 4, we found differences between the abnormal returns of the eight subsectors at the announcement. First, the Kruskal-Wallis test indicated the existence of a significant difference. Then Dunn's test indicated that Internet & Software Services suffered from significantly lower announcement returns than IT Consulting & Services and Semiconductors subsectors. In addition, the E-commerce & B2B subsector experienced significantly more positive announcement returns compared to IT Consulting & Services. These findings lead to the acceptance of hypothesis 4 that there are differences in announcement returns across the different subsectors.

Hypothesis 5 regarding post-announcement abnormal return persistence was tested along the CAAR calculations for the aggregate and each subsample. As mentioned before, we found a strong persistence of abnormal returns in the large subsample. The finding of persistence is aligned with Miles & Rosenfeld (1983), where they also found persistence of announcement returns in large divestitures.

The results of this thesis are primarily consistent with the consensus of the positive wealth effect of divestitures on the parent firms' shareholders. However, this is not always the case, as found in this paper. For example, Electronics and Software subsamples did not exhibit abnormal returns at the announcement. The Internet Software & Services subsample had significant abnormal returns measured by the market model estimation. However, the sign was negative, which is strictly against the consensus of positive divestiture announcement returns. This finding emphasizes the importance of studying and identifying sectors where the announcement returns of divestitures are negative. Answering why this happens in some sectors would increase our knowledge about divestitures. However, on the aggregate level, we accept all of the hypotheses defined for the purpose of this study.

The answer to the research questions is that divestitures in the US high-technology sector are value-enhancing and do yield an increase in shareholder wealth. When measured from the aggregate sample with the market model, the $CAAR_{0,1}$ is 1.98% ($p < 0.001, N = 318$), and with the market-adjusted method, the $CAAR_{0,1}$ is 1.80% ($p < 0.001, N = 353$).

A suggestion for future research is to adjust the scope of the event studies done regarding divestitures. For now, the research has primarily focused on regional measurements and neglected industry-specific scopes. With the industry-specific scope, it is possible to find sectors that do not follow the consensus of positive wealth effects, as demonstrated in this study. Studying sectors that depart from the consensus would increase our understanding of divestitures and the drivers of wealth effects behind them.

From a macroeconomic perspective, a similar study to this paper could be repeated to check how the post-pandemic era, with increasing policy rates, economic uncertainty, and supply chain restrictions, would affect the divestitures in the high-technology industry, their motives, and results. Also, the characteristics of the subsectors that did not exhibit abnormal returns during the announcement should be investigated in more detail — especially the Internet & Software Services subgroup, where we observed negative CAARs and negative pairwise comparisons in Dunn's test. We also suggest conducting a similar study but considering intraday complexities with intra-day price fluctuations.

6.1 Limitations

This study focused on the US sector while excluding other countries or continents. We also saw in Table 1 that the consensus about positive wealth effects is broadly researched based on the US divestitures. Therefore, while focusing on some specific sector or industry, the outlook could be made from another regional perspective, for example, with Indian or Asian high-technology divestitures.

The differences between the two datasets used for the market and market-adjusted models can bring differences between the abnormal return estimations. This difference was not considered as a significant issue since the two-model approach was robust and produced similar results despite the sample size disparity in our paper. However, more careful sample handling would be necessary if one would want to use the market model to the same extent as the market-adjusted model or another conventional normal performance model that does not require the estimation window to estimate normal return. The limitation of omitting overlapping divestiture observations with the market model approach would be avoided by clustering the standard errors of overlapping divestitures' CARs. While this would not affect the abnormal returns estimations, it would lead to more conservative test statistics and mitigation of type 1 errors.

We did not consider learning effects, despite companies having more than one divestiture during the time period of our sample. By including learning effects in the regression, we could observe the magnitude and significance of learning effects in the industry and potentially obtain a better fit for the OLS models. Also, while introducing controls for year- and subsector effects, we did not provide an inference based on those coefficients. In future research, the momentum and effect of divestiture waves could be taken into account with a more detailed approach.

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Appendix A: Market Model Variables of Interest Before Transformations and Winsorisation

Table A1: Descriptive Statistics of Market Model Variables of Interest

Note. Net-Profit-Margin (NPM), Sales to Working Capital (SWC), Current Ratio (CR), Book to Market (BM), Market Value (MV)

Variable	Mean	Std. dev.	Min	Median	Max	Skewness	Kurtosis
$CAR_{0,1}$	0.020	0.967	-0.303	0.005	0.513	1.169	8.186
NPM	-0.149	0.972	-11.978	0.168	0.459	-9.161	103.423
SWC	7.236	13.304	0.029	3.854	113.870	5.477	38.131
CR	2.609	2.344	0.970	1.862	23.945	4.685	35.890
BM	0.546	0.429	0.006	0.420	2.858	2.042	9.048
MV	242727.0.5	65477.31	4.95	1826.455	532177.6	4.227	24.957

Table A2: Descriptive Statistics of Market-Adjusted Model Variables of Interest

Note. Net-Profit-Margin (NPM), Sales to Working Capital (SWC), Current Ratio (CR), Book to Market (BM), Market Value (MV)

Variable	Mean	Std. dev.	Min	Median	Max	Skewness	Kurtosis
$CAR_{0,1}$	0.214	0.093	-0.303	0.006	0.514	1.118	8.319
NPM	-0.160	0.988	-11.978	0.174	0.459	-8.295	87.088
SWC	7.585	15.361	0.029	3.867	153.945	6.269	49.371
CR	2.601	2.427	0.970	1.825	23.934	4.419	30.715
BM	0.537	0.408	0.006	0.427	2.858	2.035	9.590
MV	22982.830	61272.130	4.95	2051.205	532177.6	4.482	28.142

Appendix B: Q-Qplots for Market and Market Adjusted CAR OLS residuals

Figure B.1: Q-Qplot of Residuals in Market Model CAR Regression

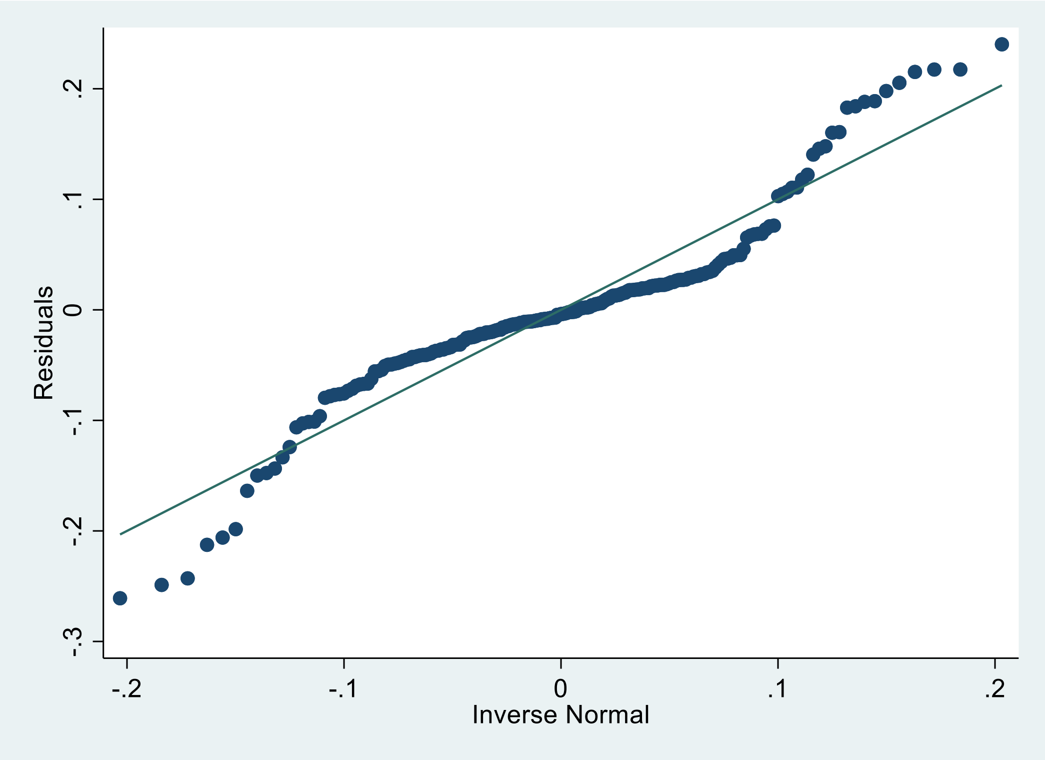

Figure B.2: Q-Qplot of Residuals in Market Adjusted Model CAR Regression