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Using the Trend: An Empirical Analysis of Whether Intangible Capital Can Enhance Abnormal Returns after Large Stock Price Movements

Author: Aarnoud Boks
Student number: 482941
Thesis supervisor: Jan Lemmen
Second reader: Eva Mulder
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PREFACE AND ACKNOWLEDGEMENTS

I want to thank everyone that has helped or supported me in any way to make this thesis.

ABSTRACT

This is a research paper on the presence of short-term under- and overreactions after large one-day share price movements, and the relation of intangible assets to these short-term events. The existence of under- and overreactions has been proved a long time ago, but the effect of intangible assets is this paper's contribution to the literature. This paper has found evidence on data ranging 2013-2022 for underreactions after large one-day stock price changes and no evidence for a significant positive or negative relation between intangible assets and the magnitude of these underreactions.

Keywords: Intangible assets, event study, abnormal return

JEL Classification: M41, B41, B41

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CHAPTER 1 Introduction

The stock market is known to be one of the most dynamic and complex financial systems in the world, with a multitude of factors influencing stock prices. One of the key drivers of stock prices is the flow of information, which can lead to significant changes in stock prices in a matter of minutes. This phenomenon has been well-documented in the literature, with studies like Bremer & Sweeney (1991) and Cox & Peterson (1994) showing that the market tends to overreact to new information, causing the stock price to move further than it should. This phenomenon presents an opportunity for regular investors to profit by buying stocks that have been oversold and selling stocks that have been overbought. But not every stock shows the same reaction, the magnitude of one-day price changes and the following under- or overreaction can differ between companies. The effect of firm size and stock exchange was incorporated in the paper by Cox & Peterson (1994). They found that small stocks had wider bid-ask spreads and were less liquid than larger stocks. These findings resulted in larger reversals for smaller stocks and after controlling for size, they found no evidence for a relation between the exchange and the degree of reversal. The overreaction effect has also been found to be larger for a portfolio of ‘loser’ stocks compared to a portfolio of ‘winners’ (de Bondt & Thaler, 1985).

So the research on overreactions has often been complemented with the effects of company characteristics, like size and stock exchange. In modern times there is an increasing amount of intangible assets, which disrupts the neoclassical view on investments (Peters & Taylor, 2017). In recent years, the US market has undergone a notable transformation, characterized by a substantial rise in technology service-oriented companies operating in science- and knowledge-based industries. This shift towards intangible assets reflects the growing importance of knowledge and innovation in today's economy. Companies that invest in intellectual property, research and development, and human capital development are increasingly gaining a competitive edge over those that rely solely on physical assets. Intangible assets provide several advantages over tangible assets, even though tangible assets remain essential in industries like construction. They are often more difficult to replicate, making it harder for competitors to imitate a company's product or service. Moreover, intangible assets can create a loyal customer base, which can lead to future sales and revenue growth. The rise of technology service-oriented companies in science- and knowledge-based industries has also led to new business models that focus on the development and monetization of intellectual property. As a result, the value of intangible assets on company balance sheets has been steadily increasing.

According to Chan, Lakonishok, and Sougiannis (2001), in 1999 the technology sector and pharmaceutical industry accounted for approximately 40% of the value of the S&P 500 index. Corrado and Hulten (2009) conducted an extensive economic analysis on the shift towards an intangible-intensive economy and estimated that intangible capital represented 34% of firms' total capital in recent years. Lev and Srivastava (2019) conducted a more recent study and found that intangible investment in the U.S. corporate sector is roughly twice that of tangible investment, and that the gap continues to grow. Therefore, it is not surprising that intangible assets are considered important resources that enable firms to attain competitive advantages.

For example, in their research article Lev & Radhakrishnan (2005) provide an all-encompassing explanation of internally generated intangibles that could potentially be capitalized. This definition includes investments in various fields such as technology, business practices, processes, designs, and incentive and compensation systems. The authors refer to this broad definition as a firm's 'organization capital.' They found that a firm-specific measure of this internally generated intangible capital plays a significant role in explaining the market value of firms. This research suggests that the development of organization capital is a crucial factor for firms to enhance their market value in the long run. Additionally, the authors findings highlight the importance of internal investments in intangible assets and the role they play in the success of firms.

The accounting of intangible assets remains a topic of debate in the literature and many papers use different calculations and proxies for intangible assets. Peters & Taylor (2017) use 30% of selling, general and administration (SG&A) minus research and development (R&D) plus 100% of R&D as investment in intangibles, while Eisfeldt & Papanikolaou (2021) argue for the use of 100% of SG&A expenditures as investments in intangible assets. This will be discussed in more length in section 4.2.

The perpetual inventory method is used by many recent papers to calculate organizational capital and knowledge capital. Both can be calculated using the perpetual inventory method, as will be discussed later on. Nowadays the research into the estimation of internally generated intangible assets goes even further, where firm and year specific measures are used to get more precise estimations (Iqbal, Rajgopal, Srivastava, & Zhao, 2022). This paper will stick to the most commonly used method until now, which is the one from Peters & Taylor (2017). This will provide comparability with past research and because of its easier application into the main research question as reflected below:

"Do stock prices overreact in the short-term and what is the effect of intangible assets on these short-term stock price movements?"

So do stocks with higher percentages of intangible assets react differently compared to companies with relatively low intangible assets to shocks and if there is an under- or overreaction, are these more or less severe than for low intangible asset stocks?

The overreaction hypothesis has been the subject of numerous studies in the past, with mixed results. Some studies have found evidence supporting the hypothesis, such as the work of DeBondt and Thaler (1985), who found that stocks performing poorly in the short-term tended to outperform in the long-term. Also, Bremer and Sweeney (1991) found that stocks experiencing a price decrease of at least 10% in one day had positive abnormal returns in the two days thereafter. Other studies did not find evidence or found evidence to the contrary, such as the work of Barberis, Shleifer, and Vishny (1998), who found that overreaction was only present in small stocks and not in large stocks. In this same paper the authors cite Cutler et al. (1991), they have shown evidence in favor of the underreaction hypothesis.

The inclusion of intangible assets is relatively new in academic literature, as leading papers from Peters & Taylor (2017) and Eisfeldt, Kim and Papanikolaou (2021) are relatively new. This, together with the division between academics on the overreaction hypothesis makes for scientifically interesting research, especially on more recent data. The research will contribute to a better understanding of what the role of intangible assets can be in the literature on the under- and overreaction hypotheses. Societally, the proposed research has significant relevance for investors seeking to make informed decisions in the stock market. The results of this study will provide insights into whether the overreaction trading strategy, complemented with a selection strategy based on intangible assets, can generate abnormal returns.

From the empirical research conducted in this paper, I find evidence for an underreaction when a stock experiences a 10% decrease or increase. The day after a 10% decrease there is a significant, negative abnormal return and after a 10% increase there is a significant, positive abnormal return. This is in line with the underreaction hypothesis, which is built on the belief that not all information is directly reflected in the stock price. The results do not show a strong relation between the abnormal return on the first day after a 10% price change and intangible assets. Only when including goodwill in intangible assets, there is a significant relation between the abnormal return after a 10% or larger decrease. Companies with higher fractions of intangible assets tend to have even larger negative abnormal returns on the day after a 10% decrease.

The rest of the paper consists of a literature review, which will shed light on the past research within this field and the existing discussion that is still present between researchers. This is followed by outlining the used data and explaining the quantitative methodology that best suits the data and the most economically and statistically relevant results are provided. Thereafter, the results with tables and figures are presented. Finally, the conclusion is provided, including a discussion on the limitations and recommendation for future research is given.

CHAPTER 2 Literature Review

2.1 The underreaction hypothesis

Barberis, Shleifer, and Vishny (1998) explain the concept of underreaction to news announcements. The authors explain that as positive news is slowly integrated into stock values, the time after a good news announcement will see higher abnormal returns. The underreaction theory is supported by empirical data, especially in the US, where firms with larger earnings surprises also generate larger returns in the time after portfolio creation (Jegadeesh & Titman, 1993). This research is based on a longer time period than the papers that find evidence for an overreaction, as they have taken a look at portfolios of winners and loser over periods ranging from 3 to 12 months. Still, while keeping this in mind, the research shows the presence of possible underreaction, which might also be present in the short-term. About a decade later, evidence of momentum in global equities markets was also discovered (Rouwenhorst, 2002). This research takes on a fairly similar approach as Jegadeesh & Titman (1993) and extends the evidence for underreactions to a global scale. The papers discussed above provide sufficient reason to believe that , within these papers' data, it is plausible to find evidence for the underreaction hypothesis.

Typically, investors underreact because they believe earnings are more stationary than they actually are. A lot of event studies have been performed on this topic and many have provided evidence in favor of the underreaction hypothesis, like the literature reviews by Daniel et al. (1998) as well as Fama (1998). In these specific meta studies, the authors go over many psychological and economic theories for both underreactions and overreactions. Even though there seems to not be a real consensus, especially in the short-term momentum strategies seem to outperform value portfolios. In the longer term it becomes harder to draw conclusions and especially older research shows stronger evidence for the implementation of a value orientated strategy. But since the research in this paper is focused on the short-term, the papers by Daniel et al. (1998) and Fama (1998) lean more towards evidence of underreactions.

Using an event study approach and a sample of firms listed on the Australian Securities Exchange, investors in the Australian stock market underreacted to coronavirus fear, supporting the gradual diffusion of information hypothesis. Naidu & Ranjeeni (2021) found evidence that investors initially underreacted to the Covid-19 outbreak, this holds true for most industries and firm sizes. A short selling strategy may have been a profitable strategy. Even though Covid-19 truly stands on its own, it is another example of an event where short-term cumulative abnormal returns could have been achieved by investors. That is why this research has led me to the first hypothesis: *Stock prices underreact to positive news and therefore show a short-term momentum effect after a 10% or more one day increase.*

2.2 The overreaction hypothesis

Overreaction occurs when investors become overly optimistic/pessimistic and send stock prices to unduly high/low levels following a series of announcements of good/bad news. An early research paper by De Bondt and Thaler (1985) uses data that goes back to before WWII and they show that a portfolio of stocks that have performed poorly over the last five years greatly outperform their counterparts that did have a good past five years. Empirical studies back up this claim, showing that overreaction to recurring news patterns undervalues companies with a history of negative news and overvalues those with a history of positive news.

Yan (2020) examines the reaction of Chinese stock markets to the COVID-19 outbreak from January to April 2020. The study finds that stock prices fell sharply with the lockdown of Wuhan city, but stock returns reversed every ten trading days throughout the event period. The study suggests that overreaction, policy response, and global supply chain interconnectedness may contribute to the frequent reversals, but larger firm size is a key factor resisting the reversals.

One of the first papers to investigate the existence of share price reversals after a large one-day decline was the paper by Bremer & Sweeney (1991), and they created the foundation on which many others have built. They found evidence for a reversal lasting approximately two days after the event date. This is an important detail for the research framework of this paper, since it will also focus on the short-term after large stock price changes. The furthest that the event window will extend to is 20 trading days following an event date. So the fact that Bremer & Sweeney (1991) find evidence for a reversal during the first two days after a large one-day price decrease gives a basis to assume that this paper might reach a similar result. The remainder of this paper will have a very similar approach to the paper by Bremer & Sweeney (1991) and Cox & Peterson (1994), so their results are important contributors to the following hypothesis: *Stock prices overreact to negative news and therefore show a short-term reversal after a 10% or more one day decrease.* Cox & Peterson (1994) also researched stock returns following one-day stock decreases of 10% or more and in their paper they conclude: “Consistent with prior studies, we find significant reversals” (Cox & Peterson, 1994, p. 267). They also mention that it really is a short-term effect and it wanes over time, which is important to keep in mind when stating such a hypothesis.

2.3 Intangible assets

Peters & Taylor (2017) find that the inclusion of intangible assets fits well into the neoclassical theory of investment, where the goals is to maximize firm value and so-called q, referring to Tobin’s Q. Tobin’s Q is a measure of a company’s profitability. Eisfeldt, Kim & Papanikolaou (2021) find that intangible assets should be considered as complementary to tangible assets and for academic purposes they use them as perfect substitutes. As this section will show, tangible and intangible assets are different and should not be regarded as one and the same. The fact that most research papers on this topic are recent and that there are still many approaches how to handle intangible assets. This shows the contemporary importance of how to incorporate intangible assets into financial research.

Since large amounts of intangible capital cannot be quantified on the balance sheet, there are different methods to estimate the value of intangible capital. This is still an innovative field with papers coming out every year that outline a different approach on how to calculate intangible assets. The basis was laid out by Peters & Taylor (2017), who first divide intangible assets into externally acquired intangible assets and internally created intangible assets. Externally acquired intangible assets are often capitalized on the balance sheet as other intangibles or goodwill and therefore needs no further calculation. Internally created intangible assets are again divided into two different kinds of assets, namely organization capital and knowledge capital, to calculate both the perpetual inventory method is used. To calculate organization capital using the perpetual inventory method one takes 30% of SG&A expenditures and to calculate knowledge capital one takes 100% of R&D expenditures. This approach, while not perfect and something that many are trying to improve upon, is still the most used approach in the available literature.

External capital consists of acquired assets following mergers and acquisitions (M&A) and are capitalized on the balance sheet as intangible capital or goodwill. M&A is more present in the tech sector and therefore there are more capitalized intangible on the balance sheet in the tech sector (Rossi, Tarba, & Raviv, 2013). The pharmaceutical industry is another industry that has seen a lot of M&A over the years and have therefore also acquired more intangible capital than other industries (Richman, Mitchell, Vidal, & Schulman, 2016).

As internal intangible assets consist of human capital, R&D, licences and patents among others, a high percentage of intangible assets is often associated with growth stocks and are therefore expected to show more volatility. At the same time it is hard to value these assets on the balance sheet, if it even ends up on the balance sheet. This feeds into information assymetry for investors, since it is hard to put a fair value on these assets. So valuations can vary a lot between analysts and this can lead to more stock price volatility (Bongaerts, Kang, & van Dijk, 2021). Gharbi, Sahut & Teulon (2014) state that increased investments in R&D leads to larger stock price volatility. The way investors perceive R&D investments changes with the market sentiment as well as the sentiment around a individual stock. If there is a bull market, a firm launches new products, firms revenue and net income keep rising, these are situations in which higher investments in R&D can lead to bigger stock price appreciation than the market. However, if there is a bear market, stagnation in profits or the R&D does not lead to new products, the R&D expenses can push a stock lower than the overall market. Leading to the third hypothesis: *Stocks with a higher percentage of intangible assets have larger market betas and therefore show more exeggarated share price movements.*

Table 1: Overview of the literature on stock price under- and overreactions

Author(s) (Publication year)	**Time period**	**Region**	**Method**	**Control variables**	**Results**
De Bondt & Thaler (1985)	1929-1982	USA	Portfolio approach	Firm size, January effect	Overreaction
Bremer & Sweeney (1991)	1962-1986	USA	Event study	-	Overreaction
Jegadeesh & Titman (1993)	1965-1989	USA	Portfolio approach	Firm size	Underreaction
Cox & Peterson (1994)	1963-1991	USA	Event study	Firm size, event day AR	Overreaction
Fama (1998)	-	-	Meta-analysis	-	Inconclusive
Daniel et al. (1998)	-	-	Event study	-	Underreaction
Rouwenhorst (1998)	1980-1995	International	Portfolio approach	Firm size, Country	Underreaction
Barberis, Shleifer, and Vishny (1998)	1960-1988	International	Psychological experiment	-	Underreaction
Yan (2020)	Jan 2020-April 2020	China	Event Study	Firm size, SOE, Ownership concentration	Overreaction
Naidu & Ranjeeni (2021)	Feb 2020-April 2020	Australia	Event Study	Firm size, Sector	Underreaction

CHAPTER 3 Data

This section will provide a description of the dataset used to test the hypotheses. It will also describe how the events of one-day price movements were selected and provide an overview of the dataset's characteristics.

3.1 Data retrieval

Firstly a dataset with data on firms in the New York Stock Exchange (NYSE) was retrieved from CRSP and Compustat – Capital IQ, which can be accessed through Wharton Research Data Services (WRDS). CRSP provides daily closing stock prices, shares outstanding, daily volume etc. Compustat provides SIC codes and firm specific financial data among others. CRSP does not provide daily total return data, however for the purpose of this research, this should not result in large complications. No distinction is made between different types of reasons for stock price movements, which mitigates the reason to use daily total return data. Even if there was a concern about certain reasons, like a dividend announcement or ex-dividend day, most of the time these would not lead to large enough price movements to trigger an event date. Then again if, for example a dividend announcement, on its own or combined with another reason does trigger an event date, it is still worth it to include this event in the research.

The NYSE was chosen, because it is a large exchange containing companies of different sizes, including mainly larger sized companies, but also medium-sized, small-sized and even micro-sized companies in different industries. The definition of micro-sized in this case is a company with a market cap below $300 million. This should provide for a dataset with enough observations and the possibility to do analyses on the industry level. The NYSE is often used in other research, speaking for its reliability and making it easier to look for comparisons between this paper and other research.

Only observations with a 10% change or more in daily closing prices are kept in the dataset. This percentage is used as the trigger percentage in the methods used by Bremer & Sweeney (1991) and Cox & Peterson (1994). Also the stock price of an individual share before the trigger event must be at least $10 or more, which is in line with Bremer & Sweeney (1991) and Cox & Peterson (1994). In order to minimize across-sample correlation, one observation per day and per company is used for both the 10% decrease sample and the 10% increase sample (Bremer & Sweeney, 1991). This means that a company and a date can occur a maximum of two times, if said company has experienced a 10% decrease and increase and if said date has a 10% decrease and a 10% increase. Furthermore, financial firms are excluded because of their usually abnormal levels of leverage, which is generally regarded a negative indicator for non-financial firms (Fama & French, 1992). Public utility companies have a link to the state, resulting in high levels of government entanglement and the business model often being influenced by the fact their goods are of high importance to the public. To summarize, the sample includes all Compustat firms, excluding regulated utilities (SIC codes 4900-4999), financial firms (6000-6999) and firms categorized as public service, international affairs, or non-operating establishments (9000+), which is common practice in the literature (Eisfeldt, Kim, & Papanikolaou, 2021 and Peters & Taylor, 2017).

The literature is not clear on the inclusion or exclusion of micro-cap stocks. Of the 476 companies in the dataset with large one day decreases there are 19 micro-cap stocks and, of the 436 in the large one-day increases, there are 26 micro-cap stocks. Since they reflect a relatively small fraction of the overall sample and the absence of reasoning to exclude in the literature, the micro-cap stocks are included in the datasets.

According to Bremer and Sweeney (1991), there are situations in which using reported returns could be biased. It's feasible for equities with extremely low prices to have significant negative rates of return, followed by reversals that just represent price oscillation between the bid and ask. As a result, only stocks with share prices of at least $10 before the event are included.

To obtain a first indication of the importance of intangible assets on the cumulative abnormal returns (CARs) following the event dates, the events are split up into groups of 20%, quintiles, with the bottom 20% containing the companies with the lowest fraction of intangible assets and the top 20% containing the companies with the highest fraction of intangible assets. These results are shown in Table 5 and provide the reader with an easy-to-understand picture of the effects of intangible assets on the magnitude of the abnormal returns.

In order to calculate the CARs, the daily closing prices of the NYSE composite are downloaded from Yahoo Finance.

3.2 Data characteristics

Table 3 below contains the descriptive company-level data. After applying the first filters, which are common practice in the corporate finance literature, like excluding certain industries, stock exchanges and winsorizing, Tables 2 and 3 show descriptive statistics. The first thing that stands out is that tangible assets on average remain larger than intangible assets and secondly the externally acquired intangibles are much larger portion of total intangibles than the internally created intangibles. This, however, is with the inclusion of goodwill in external intangibles. Goodwill is a large portion of external intangibles and when subtracting the mean and median of goodwill from the mean and median of external assets, external and internal assets become comparable in terms of size. Third, the skewness and kurtosis are quite high, which is a sign that these variables do not follow a normal distribution. Also for every variable the mean is a multiple of the median. This shows us that there remain some big outliers, even after winsorizing at the 2.5% and 97.5% level. This is why in the following statistical analyses, natural logarithms and fractions of the variables in Table 2 are used.

Table 2: Descriptive statistics

The table below shows the descriptive statistics of the company data sample retrieved from Compustat. The sample includes data from 2013-2022 for NYSE stocks, excluding industries earlier described in this section. The data is winsorized at the 2.5% and 97.5% level and Mean, Median, Std. Dev., Min. and Max. are all $1000x.

	Mean	*Median*	*Std. Dev.*	*Min.*	*Max.*	*Skewness*	*Kurtosis*	*N*
Internal intangibles	671	176	1334	0	7217	3.310	14.18	13390
External intangibles	2309	318	5140	0	26318	3.370	14.52	15550
Goodwill	1472	174	3302	0	16695	3.336	14.23	15550
Total intangibles	3110	667	6243	0	33535	3.225	13.73	13390
Tangibles	7379	1702	15710	0	96021	3.423	14.97	13390
Total assets	9980	2573	19695	0	96645	3.170	12.92	15550

In Table 3 there seems to have been a slow, but steady increase in the intangibles as a percentage of total assets. I am inclined to take the percentages from 2019 to 2021 with a grain of salt, since these are the years most affected by Covid-19 and this is known to have had a negative effect on the amount of mergers and acquisitions, which are a component of the externally acquired intangible assets. In addition, the percentage in 2013 in Table 3 might not be accurate, as it has only slightly more than a tenth of the observations compared others years. Also the average fraction of total assets in this data set is around 35%, this is in line with the 34% found by Corrado and Hulten (2009).

Table 3: Yearly statistics of intangible assets

The table below shows the percentage of Intangibles relative to total assets per year.

						Year					
Intangibles	*2013*	*2014*	*2015*	*2016*	*2017*	*2018*	*2019*	*2020*	*2021*	*2022*	*Total*
Mean	0.356	0.331	0.340	0.344	0.345	0.353	0.344	0.336	0.339	0.359	0.343
0.N	181	1576	1503	1484	1446	1421	1410	1450	1473	1265	13209

After cleaning the data as described in section 3.1, 476 events remain with a decrease of 10% or more and 436 events with an increase of 10% or more from January 1st 2013 – December 31st 2022.

Chapter 4 Method

This section of the paper will outline the research methodology. It will explain how the (CAR) is calculated, and how CARs are used to test hypotheses 1: *Stock prices underreact to positive news and therefore show a short-term momentum effect after a 10% or more one day increase.* The same method is used for testing hypothesis 2: *Stock prices overreact to negative news and therefore show a short-term reversal after a 10% or more one day decrease.* The regression model used to determine whether intangible assets have a significant impact on the cumulative abnormal return in the period after the event date will also be discussed and used to test the third hypothesis: *Stocks with a higher percentage of intangible assets have larger market betas and therefore show more exeggarated share movements.*

4.1 CAR

For the calculation of AR and CAR, the market model is used. The following states the market model formula for the normal returns with the added assumption:

$$R_{it} = \alpha_i + \beta_i R_{mt} + \varepsilon_{it} \tag{1}$$

$$E(\varepsilon_{it} = 0) \qquad var(\varepsilon_{it}) = \sigma^2,$$

where R_{it} and R_{mt} are the returns during period-t of the security and of the market and ε_{it} is the error term that is assumed to have a normal distribution (MacKinlay, 1997). A potential improvement over the simplest model, the constant mean return model, is the market model. The variance of the abnormal return is decreased by reducing the component of the return that is attributable to volatility in the market's return. Also improving upon the constant mean return model is the fact that the market model uses an estimation period to estimate alpha's and betas for each company individually. In this case I use the same estimation period as Cox & Peterson (1994), which ranges from 105 to 6 days, (-105,-6) before the event date. This can then result in a better ability to detect event consequences. The estimated alpha's and betas, expected returns are calculated per stock. By subtracting the expected returns from the actual returns the abnormal returns are calculated. Using the security and market returns, the abnormal returns can be calculated as follows:

$$AR_{it} = R_{it} - \hat{\alpha}_i - \hat{\beta}_i R_{mt} \tag{2}$$

In this case the abnormal return of a certain security is equal to the normal return minus the security specific estimated alpha minus the security specific estimated beta times the market return. The CAR can simply be calculated by summing the abnormal returns in the event window:

$$CAR_{it} = \sum_{t-5}^{t+20} AR_{it} \quad (3)$$

In the analyses I will look at the AAR on the event date and day 1, 2 and 3 thereafter. The CAAR of days 1-3, 1-20, 4-20 and -5-20 are also considered, to get a comprehensive view on the evidence for a momentum or reversal occurring.

4.2 Intangible assets

For the calculation of intangible assets, I use the same method as Peters & Taylor (2017). US accounting rules regarding intangible assets rely on whether the intangible assets were created internally or acquired externally. There is continuing innovation in this field, but as of the writing of this paper, their method is still regarded as the benchmark and is widely used in the literature.

Intangible assets generated by a company are recorded as expenses on the income statement and are rarely listed as assets on the balance sheet. For instance, a company's expenditures on research and development, patents, or software are categorized as R&D expenses. Advertising costs to establish brand value are considered selling expenses within SG&A. Employee training to enhance human capital is classified as a general or administrative expense within SG&A.

When a company acquires an intangible asset externally, e.g. through the acquisition of another company, the asset is typically recorded on the balance sheet as part of the Intangible Assets category, which includes Goodwill and Other Intangible Assets. If the acquired asset can be separately identified, such as a patent, software, or client list, it is recorded under Other Intangible Assets. Assets that cannot be separately identified, like human capital, are categorized as Goodwill. If an intangible asset becomes impaired, companies are required to reduce its recorded value on the balance sheet.

Intangible assets are defined as the sum of externally acquired intangible assets and internally created intangible assets. The former is measured as the intangible assets on the balance sheet (Compustat item *intan*). For missing values this becomes 0. Because Goodwill does contain the fair cost of acquiring intangible assets that are not independently identifiable, I continue to include those under Intangible Assets in the main analysis. For robustness, I also aim to exclude Goodwill from external intangibles because it can be tainted by non-intangibles, such as a market premium for tangible assets.

Internally created intangible assets pose a bit more difficult to quantify as they do not appear on the balance sheet. The amount of internally created intangible assets can be defined by the sum of knowledge and organization capital. Both types of capital can be calculated using the perpetual inventory method. The formula for calculating the knowledge capital is as follows:

$$K_{it} = (1-\delta_{R\&D})K_{i,t-1} + R\&D_{it} \tag{4}$$

Where K_{it} is the amount of knowledge capital on the event date, $\delta_{R\&D}$ is the depreciation rate and $R\&D_{it}$ represents the R&D expenses in that year. Normally the Bureau of Economic Analysis (BEA) industry specific depreciation rates would be used, which ranges from 10% for pharmaceuticals to 40% for computers and peripheral equipment, but Peters & Taylor (2017) found that there is almost no difference when using a fixed depreciation rate of 10%, 15% or 20%. Since Peters & Taylor (2017) and Eisfeldt, Kim and Papanikolaou (2020) used also 20% for their depreciation rate on SG&A, I elect to use the same depreciation rate on R&D. For R&D I use R&D expenses as stated on the income statement (Compustat item *xrd*) and set it to 0 when missing.

For the calculation of organization capital 30% of the SG&A expenditures is seen as investments in organization capital (Peters & Taylor, 2017), (Eisfeldt & Papanikolaou, 2014) and (Hulten & Hao, 2008) as 70% of SG&A is estimated to be operating costs for the current year. The formula then looks as follows:

$$O_{it} = (1-\delta_{SG\&A})O_{i,t-1} + 0.3SG\&A_{it} \tag{5}$$

O_{it} is the amount of organization capital on the event date, $\delta_{SG\&A}$ is the depreciation rate and $SG\&A_{it}$ represents the SG&A expenses in that year. The deprecation rate is set to 20% (Falato, Kadyrzhanova, & Steri, 2013). Calculating SG&A using Compustat entails complications as R&D and SG&A are often reported separately by companies. Nevertheless, Compustat frequently sums these respective expenses in a variable with the misleading name "Selling, General and Administrative Expense" (Compustat item *xsga*). To separate the SG&A that corporations report, subtract *xrd* from *xsga*. More specifically, subtract *xrd* and *rdip* from *xsga*. When *xrd* is a higher value than *xsga* but a lower value than *cogs*, then use *xsga* without adaptations and set missing values of *xsga* to 0 (Peters & Taylor, 2017).

This way of computing the internally created organization capital is broadly used in the available literature on intangible capital and easier to compute with Compustat data than other methods. It is in no way a perfect proxy, as there is risk of measurement error bias, but by performing the analysis also without the inclusion of goodwill I aim to add additional robustness to the results. As seen in section 3.2, goodwill was a large portion of the total intangible assets and as there are arguments in the literature arguing that goodwill has a disruptive effect on the effects of intangible assets, I will also perform the same regression analyses excluding goodwill from the externally acquired intangible assets.

4.3 OLS regression

With the following regression analysis, I want to find out whether high amounts of intangible capital are of significant influence on the large stock price changes and the following under- and overreactions. Equation (*6)* is inspired by Cox & Peterson (1994), who use the same type of formula to perform their research of influencing factors on CAR. They, however, did not include market-to-book ratio and the reasoning behind that eludes me. But with the knowledge from the earlier mentioned research, it is quite likely that market-to-book ratio has some relation to the fraction of intangible capital, as not all intangible assets are capitalized on the balance sheet, but the market could recognize its value. So for some of the analyses market-to-book ratio will be included as a deviation from the method by Cox & Peterson (1994). This formula is also the way in which I generate the results to test hypothesis 3: *Stocks with a higher percentage of intangible assets have larger market betas and therefore show more exeggarated share movements*.

$$CAR_i = \alpha + \beta_1 AR0_i + \beta_2 SIZE_i + \beta_3 M/B_i + \beta_3 INT_i + \varepsilon_{i.} \qquad (6)$$

Where,

CAR_i = the post large price movement cumulative abnormal return for security *i*,

$AR0_i$ = the event day abnormal return for security *i*,

$SIZE_i$ = the natural logarithm of the market capitalization of security *i*, 6 days prior to the event date,

M/B_i = the market-to-book ratio of security *i*, 6 days prior to the event date,

INT_i = the fraction of total assets that is intangible,

ε_i = the error term for security *i.*

4.4 Industry and year effects

As explained in the Chapter 2, intangible assets tend to be more present in certain industries compared to others, examples of industries that tend to have higher fractions of intangible assets are tech and pharmaceuticals. In order to address this and get more robust results, dummy variables are constructed following the Fama and French 12 industry classification, *Appendix A.* This is a way to analyse whether any effects of intangible assets on CAR were due to industry and not necessarily intangible assets. Since industry could have an effect of both our dependent and independent variable, the inclusion of these dummies also addresses endogeneity, which is an everlasting problem in this type of research, but these measures diminish the effects of endogeneity. Adding to this, the use of year fixed effects takes out the heterogeneity that might have been present between the sample years and bolsters the results of the regressions.

$$CAR_i = \alpha + \beta_1 AR0_i + \beta_2 SIZE_i + \beta_3 INT_i + \beta_4 YearFE + \sum_{i'=1}^{10} \beta_{i'} Industry_{i \cdot i'} + \varepsilon_i \qquad (7)$$

CHAPTER 5 Results

In this section the results from the various analyses will be discussed. Starting with the evidence found for the under- and/or overreaction hypotheses. To give a first impression of the influence of intangible assets, five different event studies on portfolios were performed. These portfolios were constructed on the basis of the fraction of intangible assets. Followed by the results of OLS regressions on the CARs, with the inclusion of the independent variable of interest, intangible assets as a fraction of total assets, and two control variables, which are part of the five Fama and French factors, size and market-to-book ratio.

5.1 Momentum

To test for hypothesis 1: *Stock prices underreact to positive news and therefore show a short-term momentum effect after a 10% or more one day increase,* the results are presented in Table 4. For this section the results in the third and fourth column are used. The AAR on day 1 is 2.63% and statistically significant at the 1% level, which provides evidence of a momentum in the short-term. The AAR on day 2 is not significant, but the AAR on day 3 is 0.9% and statistically significant at the 10% level, giving weak evidence for a continuation of the price movement on day 3. The CAAR for days 1-3 is 2.89% and statistically significant at the 1% level, mostly driven by day 1 and slightly by day 3. The CAAR for days 4-20 is -1.2% and not statistically significant. From the results in the third and fourth column of Table 3 a definite one day continuation can be observed, a weak continuation on the third day and no statistical evidence beyond that. Also when looking at Figure 1, the AAR on day 1 is a continuation of the direction on day 0, and after that the CAAR remains flat. Based on this evidence, I reject the null-hypothesis of there not being a momentum effect following the results in Table 4.

5.2 Reversal

To test for hypothesis 2: *Stock prices overreact to negative news and therefore show a short-term reversal after a 10% or more one day decrease,* the results are presented in Table 4. For this section the results in the first and second column are used. The AAR on day 1 is -2.81%, the result is statistically significant at the 1% level and provides evidence of a momentum in the short-term. The CAAR for days 1-3 is -3% and is statistically significant at the 1% level. However, this is driven by the AAR of day one, since days 2 and 3 have small coefficients that are not statistically significant. The CAAR for days 4-20 is -1.06% and not statistically significant. To summarize, the results of the first two columns of Table 4 show that there is a continuation on day 1 of the stock price movement on day 0, which fades away on day 2. This becomes even more clear in Figure 1, showing that there is a notable continuation on day 1 of the direction that was set on day 0, but that after day 1, the CAAR remains flat. Based on these results, I reject hypothesis 2, which means that there is not a short-term reversal after a large one-day price decrease. On the contrary Table 4 provides evidence for a momentum in the short-term.

Table 4: CAR data on the day of a 10% or larger price increase and decrease and the short-term period thereafter

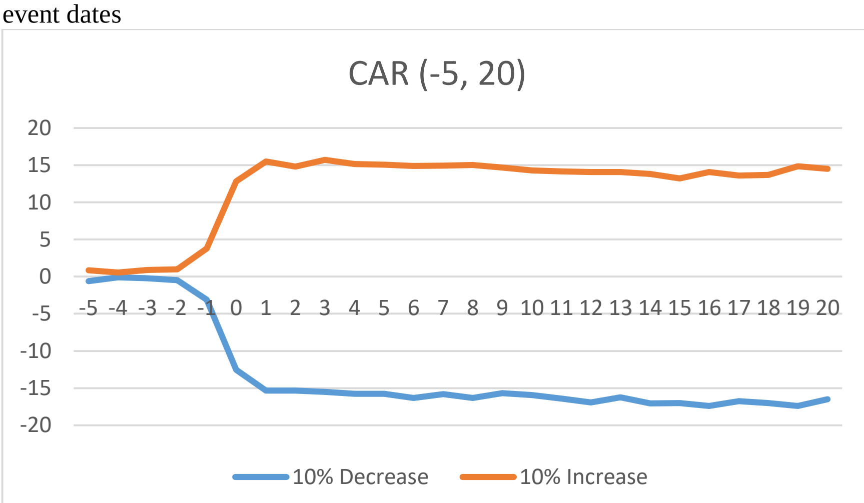
The table below shows the characteristics of two datasets for a time period starting January 1st 2013 to December 31st 2022. The AARs are equal to the average of every security return minus its estimated alpha and estimated beta times the market return. The CAARs are the sum of the AARs over the specified event period. The estimation period is from 105 trading days before the event date until 6 days before the event date (-105,-6).

	-10% (n = 476)	t-statistic	+10% (n = 436)	t-statistic
AAR Day 0	-9.43%***	-21.66	9.07%***	18.74
AAR Day 1	-2.81%***	-6.40	2.63%***	5.37
AAR Day 2	0.01%	0.01	-0.65%	-1.36
AAR Day 3	-0.19%	-0.44	0.90%*	1.88
CAAR Day 1-3	-3.00%***	-3.92	2.89%***	3.046
CAAR Day 1-20	-4.02%*	-1.83	1.77%	0.79
CAAR Day 4-20	-1.06%	-0.54	-1.19%	-0.58
CAAR Day -5-20	-16.35%***	-6.03	14.47%***	5.40

*Indicates significance at the 10% level
**Indicates significance at the 5% level
***Indicates significance at the 1% level

Figure 1: Cumulative Abnormal Return around event dates (t=0) of large one day price changes

The figure below shows the cumulative abnormal return in percentages from 5 days before until 20 days after the event dates



5.3 Regression analyses

To test for hypothesis 3: *Stocks with a higher percentage of intangible assets have larger market betas and therefore show more exeggarated share movements,* the results are presented in Tables 5, 6 and 7. Firstly, when looking at Table 5, one should take a look and search for a relation that can be witnessed intuitively without using a statistical test. By doing so, an expectation of the other test results is created and one should think twice whether the results contradict the expectation completely. When looking at Table 5, larger coefficients for the higher quintiles in column 3 can be observed, the other columns do not tend to show a relation between the different quintiles and the magnitude of the AARs. So when performing the regressions to establish whether there is a significant relation between intangible assets and price movements after a big one-day price decrease and increase, the expectation is that there could only be a significant correlation with the AAR on the first day after a big one-day price decrease.

One can also observe in column 2, that the highest AAR on day 0 for large one-day price increases has a lower AAR on day 1, column 4. This gives the suspicion of a negative relation between the price increase on day 0 and the price increase on day 1.

Table 5: Quintile portfolio performance

The table below shows the results of the event study in Table 4, but then divided in tranches of 20%. Quintile 1 contains the bottom 20% of companies based on the fraction of intangible assets of total assets, Quintile 5 contains the companies with the highest percentage of intangible assets. The coefficients are the AARs on the first day after the event (t=1) Time period and estimation period are the same as for Table 4.

	Day 0		Day 1	
	-10%	+10%	-10%	+10%
Quintile 1	-9.91%***	6.78%***	-1.65%***	2.57%***
Quintile 2	-9.77%***	12.62%***	-0.05%	2.07%
Quintile 3	-8.18%***	9.14%***	-5.14%***	2.92%***
Quintile 4	-11.12%***	9.67%***	-3.10%***	2.15***
Quintile 5	-8.07%***	7.21%***	-4.52%***	3.44%***

*Indicates significance at the 10% level
**Indicates significance at the 5% level
***Indicates significance at the 1% level

In Table 6 are the main results of the research, and the expectations from the previous paragraph are confirmed by these results. When looking at column 1, which is the simple OLS regression on the AAR after a large one-day decrease, intangible assets have a significant negative effect when controlling for the event day abnormal return and company size. In column 2 there is even a small increase in the magnitude of the coefficient and the t-value, which means that controlling for industry and year effects makes no significant difference to the explanatory power of intangible assets. The inclusion of the control variable for market-to-book ratio did take away a bit of the significance of intangible assets. Since I am only interested in the relation between the dependent variable and intangible assets, I find the F-value and R^2 of lesser importance. These values would be of higher importance if my objective was to precisely predict the dependent variable. However, since the R^2 is above 0.1, there is some explanatory power present in the regression models. Interestingly, the inclusion of the industry dummies and the year fixed effects did not add a lot to the R^2. Most of the stock price movement of day 1 is predicted by the movement on day 0, this coefficient is consistently c. 10 times larger than the coefficient for intangible assets. Hence, when looking for abnormal returns using a short selling strategy, it is more important to find stocks with large one-day decreases, and, if possible, pick the ones with higher fractions of intangible assets. Also important to note is that there are some significant differences between industries. Telecommunications has a significant effect on the day 1 AR compared to most other industries. After a large one-day decrease, Telecommunications has a dampening effect on the continuation on the first day thereafter. Therefore, when betting on this one day continuation of the direction of the stock, it would be recommended to avoid telecommunication companies. In the presented tables after Table 6, the industries will be added as fixed effects, which is similar to adding all industries dummies.

In line with the expectations based on Table 5, intangible assets do not hold significant explanatory power on the price movements after a large one-day increase in share price, as can be seen in Table 6. There is, however, a strong significant correlation between the AR on day 0 and the AR on day 1. For all six columns, a negative relation is observed between the day 1 AR and the day 0 AR. For columns 1 to 3 this means that if the AR on day 0 becomes more negative, the AR on day 1 becomes less negative. For columns 4 to 6 this means that if the AR on day 0 becomes more positive, the AR on day 1 becomes less positive. This is a surprising result, however, when there is a price change of 10% or more, one should look at how much of that is explained by the abnormal return and how much of the price change was driven by the market. Subsequently choose the ones with the lowest abnormal return on the event day for the biggest potential gains on the day thereafter.

Table 6: OLS regressions

The table below shows the results of multiple regressions on the average abnormal return on the first day after an event date. Columns 1 and 4 are simple OLS regressions with independent variables: event day abnormal return (AR0), a size variable based on the natural logarithm of market cap (SIZE), market-to-book ratio constructed by dividing the market cap by the book value (*M/B*), and the fraction of total assets that are intangibles (INT). Columns 2, 3, 5 and 6 have added industry effects through dummy variables for every industry and year fixed effects. T-values can be found in the parentheses. Industries were constructed using the Fama and French classification, available on the website of Kenneth French. (http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html)

	Day 1					
		-10%			*10%*	
	(1)	*(2)*	*(3)*	*(4)*	*(5)*	*(6)*
Intercept	0.101	0.104	0.104	0.104*	0.150***	0.155***
	(0.88)	(0.94)	(0.95)	(1.88)	(2.87)	(2.93)
AR0	-0.570**	-0.574**	-0.578**	-0.337***	-0.344***	-0.344***
	(-2.14)	(-2.22)	(-2.21)	(-3.96)	(-4.20)	(-4.20)
SIZE	-0.008	-0.009	-0.009	-0.002	-0.003	-0.003
	(-1.29)	(-1.41)	(-1.41)	(-1.01)	(-1.14)	(-1.17)
M/B			0.000			0.000
			(1.48)			(1.09)
INT	-0.045**	0.051**	-0.051**	0.015	0.006	0.005
	(-2.06)	(-2.13)	(-2.10)	(1.09)	(0.36)	(0.32)
Consumer Non-durables		0.035	0.035		0.027	0.027
		(1.43)	(1.41)		(1.53)	(1.55)
Consumer Durables		0.017	0.025		-0.005	-0.001
		(0.81)	(1.13)		(-0.22)	(-0.03)
Manufacturing		0.018	0.018		0.020*	0.020*
		(1.29)	(1.29)		(1.90)	(1.90)
Energy		0.010	0.010		-0.003	-0.003
		(0.61)	(0.65)		(-0.25)	(-0.25)
Chemicals		-0.001	-0.001		0.004	0.004
		(-0.03)	(-0.05)		(0.24)	(0.27)
Business Equipment		-0.004	-0.005		0.007	0.007
		(-0.27)	(-0.28)		(0.68)	(0.66)
Telecommunications		0.073**	0.073**		0.004	0.004
		(2.54)	(2.55)		(0.23)	(0.25)
Shops		0.022	0.023		0.018	0.020
		(0.71)	(0.70)		(1.10)	(1.19)
Healthcare		0.043*	0.043*		0.007	0.007
		(1.71)	(1.69)		(0.46)	(0.46)
Other		0	0		0	0
		-	-		-	-
Year Fixed Effects	No	Yes	Yes	No	Yes	Yes
F-value	2.40	1.38	1.34	6.17	2.38	2.32
R^2	0.295	0.331	0.331	0.430	0.455	0.457
Adj. R^2	0.290	0.299	0.298	0.426	0.427	0.427

*Indicates significance at the 10% level
**Indicates significance at the 5% level
***Indicates significance at the 1% level

Table 7: OLS regressions excluding goodwill
The table below shows the results of multiple regressions on the average abnormal return on the first day after an event date. Independent variables: event day abnormal return (*AR0*), a size variable based on the natural logarithm of market cap (*SIZE*), market-to-book ratio constructed by dividing the market cap by the book value (*M/B*), and the fraction of total assets that are intangibles minus goodwill (*INTWG*). All regressions now have added industry and year fixed effects T-values can be found in the parentheses. Industries were constructed using the Fama and French classification, available on the website of Kenneth French.
(http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html)

	Day 1					
		-10%			*10%*	
	(1)	*(2)*	*(3)*	*(4)*	*(5)*	*(6)*
Intercept	0.149	0.149	0.113	0.180***	0.186***	0.185***
	(1.13)	(1.13)	(0.94)	(3.37)	(3.44)	(3.41)
AR0	-0.577**	-0.580**	-0.576**	-0.344***	-0.345***	-0.345***
	(-2.23)	(-2.22)	(-2.17)	(-4.22)	(-4.22)	(-4.23)
SIZE	-0.009	-0.009	-0.008	-0.003	-0.003	-0.003
	(-1.47)	(-1.47)	(-1.25)	(-1.14)	(-1.17)	(-1.28)
M/B		0.000	0.000		0.000	0.000
		(1.56)	(1.52)		(1.10)	(1.13)
INTWG	-0.053	-0.053		-0.003	-0.004	
	(-1.33)	(-1.31)		(-0.10)	(-0.15)	
Goodwill			-0.068			0.019
			(-1.37)			(0.63)
Industry Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
F-Value	1.34	1.31	1.37	2.41	2.36	2.49
R^2	0.329	0.329	0.329	0.455	0.456	0.457
Adj. R^2	0.297	0.295	0.295	0.427	0.427	0.428

*Indicates significance at the 10% level
**Indicates significance at the 5% level
***Indicates significance at the 1% level

As mentioned in earlier sections, goodwill is an item that is far from being undisputed in the literature. This is why I have performed the same OLS regression without the goodwill included in intangible assets, for which the results are shown in Table 7. The variable for intangible assets becomes insignificant across the board because of this change. This result does not add robustness to the previous findings, but it does raise the question on whether goodwill in itself might have some explanatory power on the day 1 AR. So in Columns 3 and 6 of Table 7, I have excluded all other intangible assets and just left goodwill as the independent variable of interest. It can be seen that goodwill has a negative coefficient in column 3 and positive in coefficient in column 6, but it is not significant. In Table 7, columns 1-3, it does show that intangibles excluding goodwill and goodwill on a stand-alone basis have relatively high t-values. This is likely the reason that, together the variable they had a statistically significant coefficient in Table 6.

Now when it comes to the third hypothesis: *Stocks with a higher percentage of intangible assets have larger market betas and therefore show more exeggarated share movements*, I reject this hypothesis, stocks with larger fractions of intangible assets do not show more exeggarated share movements. The strongest evidence in favor of the hypothesis is found in Table 6, columns 1 and 2 being significant at the 5% level and column 3 at the 10% level. This only supports the hypothesis in case of large one-day stock price decreases, but that is only half of the research framework and since intangible assets without goodwill lost its significance entirely.

CHAPTER 6 Conclusion and limitations

6.1 Conclusion

This paper started off with the following research question: *"Do stock prices overreact in the short-term and what is the effect of intangible assets on these short-term stock price movements?"* This research question followed from the curiosity of a contemporary phenomenon of increasing amounts of intangible capital with relation to a research topic that is much older than the research on intangible assets, under- and overreactions on the stock market.

In search of a final answer to this question I started by performing research for the first hypothesis: *Stock prices underreact to positive news and therefore show a short-term momentum effect after a 10% or more one day increase.* This hypothesis cannot be rejected based on the evidence found and therefore is not affirmative to the first part of the research question.

Continuing the research on the second hypothesis: *Stock prices overreact to negative news and therefore show a short-term reversal after a 10% or more one day decrease,* the results from the statistical analyses pointed towards the opposite. Stocks show a short-term momentum after a large increase as well as a decrease, so the second hypothesis can be rejected.

Finally the third hypothesis: *Stocks with a higher percentage of intangible assets have larger market betas and therefore show more exeggarated share movements;* although the results are less clear, the ultimate conclusion for this hypothesis was to reject it. In the first analysis there was evidence for a significant effect of intangible assets on the price movement on the first day after a large price decrease, but any evidence for price increases was already lacking. The inclusion of the *M/B* variable provided an even less significant coefficient, and after performing a robustness analysis, the intangible assets lost all of its significant explanatory power.

To give a final answer to my research question; no, stock prices do not seem to overreact in the short-term, with evidence showing the opposite. The effect of intangible assets on this underreaction is rather small and mostly insignificant.

6.2 Limitations

Finally, as any paper, there are numerous limitations to the analyses performed. For instance, CRSP only had daily open and closing prices available and not price index return data, which would have controlled for transaction costs and the possibility of stock splits, ex-dividend dates etc. The purpose of this research was mainly focussed on the effects of intangible assets after large stock price changes, so this limitation probably was not detrimental. Goodwill remains a difficult item in these analyses, how to value it and whether to include it or not. Future research might try even more methods regarding the calculation of intangible assets and goodwill. If future research might focus on a profitable investment strategy, then this is something to consider. For purposes mentioned in section 3.1, I have only used stocks from one exchange. For more robust results a future paper might elect to include more exchanges and look for geographical differences. For calculation of CAR, I only used the market model, a more advanced calculation like the FF5F model can be used. However, this is known to have very little effect and is unlikely to change the outcomes significantly. This might only add a little bit of robustness.

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APPENDIX A Fama and French 12 industry classification

1 NoDur Consumer Nondurables -- Food, Tobacco, Textiles, Apparel, Leather, Toys:

0100-0999, 2000-2399, 2700-2749, 2770-2799, 3100-3199, 3940-3989

2 Durbl Consumer Durables -- Cars, TVs, Furniture, Household Appliances:

2500-2519, 2590-2599, 3630-3659, 3710-3711, 3714-3714, 3716-3716, 3750-3751, 3792-3792, 3900-3939, 3990-3999

3 Manuf Manufacturing -- Machinery, Trucks, Planes, Off Furn, Paper, Com Printing:

2520-2589, 2600-2699, 2750-2769, 3000-3099, 3200-3569, 3580-3629, 3700-3709, 3712-3713, 3715-3715, 3717-3749, 3752-3791, 3793-3799, 3830-3839, 3860-3899

4 Enrgy Oil, Gas, and Coal Extraction and Products:

1200-1399, 2900-2999

5 Chems Chemicals and Allied Products:

2800-2829, 2840-2899

6 BusEq Business Equipment -- Computers, Software, and Electronic Equipment:

3570-3579, 3660-3692, 3694-3699, 3810-3829, 7370-7379

7 Telcm Telephone and Television Transmission:

4800-4899

8 Utils Utilities:

4900-4949

9 Shops Wholesale, Retail, and Some Services (Laundries, Repair Shops):

5000-5999, 7200-7299, 7600-7699

10 Hlth   Healthcare, Medical Equipment, and Drugs:

2830-2839, 3693-3693, 3840-3859, 8000-8099

11 Money Finance:

6000-6999

12 Other Other -- Mines, Constr, BldMt, Trans, Hotels, Bus Serv, Entertainment: