Dual-class Stocks in the Technology Sector

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An Asset Pricing Study*

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Abstract

This thesis analyses how dual-class structures impact stock performance in the U.S. Technology sector. By examining this specific sector, a niche intra-industry approach is adopted, which distinguishes the study from previous research within the field of dual-class stocks. Dual-class offerings are increasingly popular within the Technology industry, which in turn is driving regulatory change in favour of the controversial structure. Two matched portfolios are created in our study, one consisting of single-class firms and one consisting of dual-class firms. By using the Carhart four-factor regression model we investigate trends and differences between the two portfolios' performances. The resulting dual-class coefficients experience a larger spread and a greater divergence in regression characteristics, in contrast to the more stable single-class equivalents. The measured abnormal returns for the individual portfolios are similar albeit the t-statistics are low. When constructing a trading strategy based on the significant market risk coefficient, positive abnormal returns can be achieved at a significance level of 10%. Based on our findings, there is not sufficient evidence to confirm the conception that dual-class structures are generally negative for outside shareholders. Furthermore, we argue that industry-specific factors are likely to be important pieces of the dual-class performance puzzle.

Keywords: Asset Pricing, Dual-Class Stocks, Technology Sector, Controlling-Minority Structure, Trading Strategy.

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1. Introduction

In today's modern economy, the corporate ownership structures often deviate from the simple "one share – one vote" system. More complex public offerings using multiple voting classes, non-voting shares and convertibles are becoming increasingly popular in certain regions and industries. These structures create a controversial discrepancy between cash flow rights and voting rights by allowing minority shareholders to retain beneficial ownership and operational control of a company, while simultaneously being able to increase the size of capital raising transactions in equity markets.[3]

Executive management at dual-class-structured firms emphasize the fact that the structure enables them to maintain long-term control of the business, without necessarily holding a majority stake in the company. It allows founders to ignore quarterly earnings expectations and short-term market profit requirements from majority shareholders, while at the same time raising sufficient capital to support their own vision. In addition, the dual-class structure provides levels of insider protection against hostile takeover attempts.

On the flip side, it is hardly a surprise that dual-class offerings are surrounded by market controversy and fragile investor appetite. Dual-class opposition argue that capital providers should have a voice in how a company is run. For example, Snap Inc. received several of protest letters from several of the largest pension funds, as it was the first U.S. initial public offering to exclusively issue non-voting shares to the public (*Reuters*, 2017 and *Securities and Exchange Commission*, 2017).

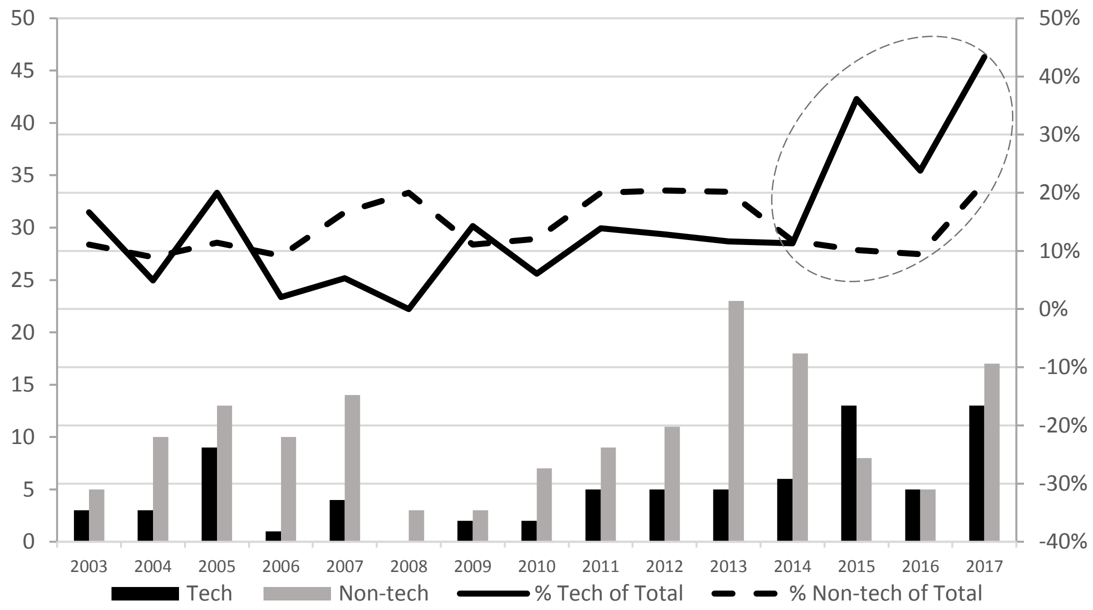
The regulatory restrictions vary greatly across the world, where many locations prohibit the listing of dual-class shares. The increasing popularity of listing dual-class share structures has created pressure for regulatory change amongst stock exchanges. It was recently reported that Hong Kong's exchange, HKEX, has implemented major changes in regulations to adopt a system that enables dispersion in ownership through dual-class shares (*Bloomberg*, 2018). These changes are considered as a reaction to maintain attractiveness towards technology firms and their founders that seek to raise new equity without losing control. It can further be viewed as a response towards losing out on initial public offerings such as that of Alibaba Group Holding Ltd. who chose to hold its USD 25bn initial share sale with a dual-class structure on the NYSE (*Bloomberg*, 2017).

This thesis builds upon the work of recognised papers, including Paul A. Gompers et al. (2009), which analyse the relationship between insider ownership and firm value, as well as the

[3] For simplicity reasons, this thesis refers to all multiple voting structures as dual-class.

impact of dual-class structures on stock performance. What distinguishes this thesis from earlier research on the topic of dual-class structures and their impact on performance, is its sole focus on the U.S. Information Technology sector.[4] The industry has been the host of many dual-class IPOs of familiar companies such as Snap Inc., Alibaba Group Holding Ltd. and LinkedIn Corp. Looking at the data provided for initial public offerings in the United States by Jay R. Ritter at the University of Florida (2018), it is evident that the trend of dual-class listings is especially strong for technology firms (see Figure 1). Public offerings for dual-class companies within technology have during the past three years constituted for a larger fraction of total IPOs in the sector compared to the fraction of all other sectors. The trend further motivates why it is of interest to focus on stock performance within the Technology sector.

Figure 1: U.S. dual-class IPOs by sector



Notes: Figure 1 lists the number and percentage of annual IPOs that have dual-class share structures amongst Technology IPOs and amongst Non-Technology IPOs. The lines display the fraction of dual-class IPOs in relation to total IPOs per category. The bars illustrate the number of dual-class IPOs per category. The data is based on IPOs with an offer price of at least USD 5.00, excluding ADRs, unit offers, closed-end funds, REITs, natural resource limited partnerships, small best efforts offers, banks and S&Ls, and stocks not listed on AMEX, NYSE, and NASDAQ.

The common academic conception is that managerial entrenchment reduces shareholder value. Dual-class structures increase the risk of managerial entrenchment due to disproportionate insider control and protection. As a result, research claims that these structures

[4] The GICS distinguishes between two main types of Technology sectors: Information Technology and Telecom.

on average lead to negative abnormal returns. However, recent studies have claimed the abnormal returns to be non-significant. Thus, given that a dual-class structure generally is believed to reduce intrinsic firm value, this thesis aims to examine what the case is for these types of stocks within the trending Technology industry?[5]

The excess return regressions used in this asset pricing study yield time-varying coefficients, which enables the study of prevalent trends and comparison for how regression coefficients change over time for single- and dual-class companies. Building on these results, we ask ourselves if it is possible to devise a trading strategy, using the trends regarding single- and dual-class stock behaviours.

In order to analyse differences across different firm types, one dual-class and equivalent single-class equal-weighted portfolio are created. Regressing the portfolios' excess returns in relation to the Carhart four-factor model shows how dual-class stocks vary more in performance and tend to covary with the markets to a greater extent during times of low volatility (compared to when volatility is relatively higher). The results are used to create a trading strategy of buying dual-class shares during relatively low volatility (based on a VIX-measurement) and adversely going long single-class shares during relatively high volatility. Implementing the strategy between 2013 and 2017 yields daily abnormal returns at a significance level of 10%[6], which further highlights differences between dual- and single-class stocks.

[5] Excluding Telecom.
[6] Precise significance level of 5.5%.

2. Related Literature

Dual-class share structures are according to Bebchuck et al. (2000) defined as one out of three principal ways for exhibiting “controlling-minority structure” (CMS). It permits strong ownership control while holding only a fraction of equity. The relationship is believed to be that decreasing amounts of cash-flow rights held in relation to control rights sharply increases agency costs, as costs of moral hazard can be progressively more externalized (ibid.). Gompers et al. (2003) provide useful information on the performance of dual-class firms as they analyse how corporate governance variables and shareholder rights affects firm value and performance. They find that firms with more equal shareholder rights experience higher firm value, profits and sales growth, as well as lower capital expenditures and fewer corporate acquisitions.

Bebchuk et al. (2008) continue the study of corporate governance variables. They use provisions from the Gompers et al. (2003) governance index including, but not limited to, staggered boards and golden parachutes. Their findings align with the results of Gompers et al. (2003), as they conclude that increased index levels are correlated with decreased firm values and negative abnormal returns. A trading strategy is devised based on buying firms with low index scores while short selling firms with high index scores, which resulted in abnormal returns of 7% in the period 1990-2003.

Gompers et al. (2009) build upon the approach discussed in the paragraph above and examine whether a dual-class structure is correlated with returns, using a Carhart four-factor regression and a sample period between July 1995 and June 2003. In the sample, they find no clear pattern to returns and argue that a possible explanation to why this result differs from the previous studies is that the dual-class feature might be fully incorporated into stock prices by the beginning of their sample period.

Regarding agency problems and operating performance of dual-class companies, Masulis et al. (2009) conclude that firm value decreases as the divergence between insider control rights and cash-flow rights widens, based on a sample of U.S. firms. They argue that agency problems arise to a greater extent when management teams have a disproportionately high number of control rights over cash-flow rights. In turn, as managers seek personal benefits at the expense of outside shareholders, performance metrics and stock returns are lowered. There are at the same time, as pointed out by Bebchuck et al. (2000), potential constraints to the agency problems, such as reputation. Sound managerial reputation may be required if CMS controllers wish to avoid paying the price of expected agency costs for their dual-class firms when returning for additional funding through the capital markets.

Looking at the situation from a managerial perspective, the works of Michael Maccoby can serve for explaining how corporate control and leadership characteristics may influence company performance. Maccoby wrote an article regarding what is defined as “Narcissistic leaders” during the beginning of the 21st century as the Information Technology sector was booming. Narcissists are a personality type that is characterized by innovators who are driven to gain power and glory. A productive narcissist is an expert within their industry that is willing to learn everything that affects their company and their products. Great visions and charisma make narcissists thrive in highly changing environments and makes it a reason for why many narcissistic leaders can be identified within the Technology sector. However, oversensitivity to criticism, lack of empathy and strong distrust can result in a narcissistic leader having an adverse effect on a company (Maccoby, 2004). It is debatable if the benefits outweigh the disadvantages, but what is for certain is that narcissistic leaders in dual-class companies may have more power and better abilities to influence as the divergent share class structure makes it possible to retain stronger control of a company. A discrepancy between cash flow rights and voting rights would make it easier for these narcissists to mitigate the risk of being influenced by public shareholders or lose control of their companies.

As the main purpose of this paper is to analyse the impact of dual-class structures on stock market returns within the Technology sector, it is relevant to study and apply the findings of Böhmer et al. (1995). They research performance differences related to firms’ ownership structures and document a sample of 98 dual-class companies outperforming a matching sample of single-class companies. Findings do however not include any statistically significant abnormal long-term performance associated with dual-class. These differences in results may stem from a number of different factors including, but not limited to, investment horizons, period in time and sample specifics.

The related literature above is of great relevance for the upcoming sections. The methodology of choice builds on previously mentioned papers in terms of sampling, portfolio matching for single- and dual-class firms and regression variables, while simultaneously establishing a specific focus on technology firms.

3. Data

3.1. Initial Data

In order to make the analysis as complete as possible, the initial data screening is focused on a developed economy with strong financial markets where dual-class public companies exist and are not uncommon. Looking at available data, it is apparent that the U.S. financial markets offer a beneficial landscape for securities analysis as U.S. markets are extensively covered in available databases. In addition, data from the Center for Research in Security Prices, CRSP, can be used as a reliable source for tracking historical returns of American securities.

An initial screening through Bloomberg consisting of the 10,000 largest public companies listed on major U.S. stock exchanges, based on market capitalization as of 1 March 2018, is analysed to map the prevalence of dual-class companies across different industries. The screening shows that sectors such as Diversified Industries, Communications, and Cyclical Consumer Industries (highlighted below) contain a considerable number of dual-class companies. Results from the screening for all sectors are presented in Table 1.

Table 1: Prevalence of dual-class shares – industry breakdown

	Single-class	Dual-class	Total	Percentage Dual-class
Basic Materials	363	13	376	3.5%
Communications	576	97	673	14.4%
Consumer, C	661	80	741	10.8%
Consumer, NC	1699	64	1763	3.6%
Diversified	90	18	108	16.7%
Energy	531	49	580	8.4%
Financial	1875	112	1987	5.6%
Funds	2161	0	2161	0.0%
Government	1	1	2	50.0%
Industrial	847	46	893	5.2%
Technology	583	39	622	6.3%
Utilities	87	7	94	7.4%
Total	9474	526	10000	5.3%

Notes: Breakdown of existence of dual-class shares amongst the 10,000 largest listed companies in the U.S. as of beginning of March 2018. Data is collected from Bloomberg and industry classification is based on the Bloomberg Industry Classification System (BICS) and the technology firms of interest for the study can thus, in this classification, be found both within the "Technology" and the "Communications" sector. C denotes cyclical and NC denotes non-cyclical for the consumer industries. The highlighted industries contain a large fraction of dual-class firms (excluding Government due to its small number of firms).

Table 1 indicates a larger than average fraction of dual-class firms being present within a combination of Technology and Communications. These two industries can, due to their similarities in the Bloomberg Industry Classification System, be viewed as one combined sector. The combined sector includes large and well-known offerings such as Snap Inc., Alibaba Group Holdings Ltd. and Alphabet Inc. Focusing the analysis within a specific industry definition makes it possible to eliminate differences in industry-specific factors affecting share performance. To facilitate an efficient data gathering, the remainder of the paper focuses on the Global Industry Classification Standard (GICS) defined "Information Technology sector" (sector group code 45).[7] The GICS uses a more standardised taxonomy compared to the BICS, while simultaneously using one sector to include the firms of interest captured in both Technology and Communications in Table 1. The sector has a large number of dual-class firms, but is also characterised as a highly competitive industry. Because the business nature of the Technology industry requires a strong ability to adapt to frequent change, it is interesting to analyse and compare single- and dual-class firms in terms of how differences in voting structures translate into stock performance effects.

Based on the selection of the Technology sector for analysis, a narrowed screening is conducted. After screening for all firms that are classified as being within the Information Technology sector according to the Global Industry Classification Standard, 1,070 firms remain out of the largest 10,000. Out of the remaining 1,070, a current market capitalization lower limit is set to USD 10 million and exchanges are limited to the main three (NYSE, NASDAQ and AMEX). Limiting the scope to the main three exchanges creates a focus on liquid stocks that are easily accessible for investors. The result is 667 firms remaining and out of these firms 54 can be identified as dual-class. As the methodology (see page12) uses data up until the end of 2017, a minimum requirement of at least one year of available returns per firm is set in order to establish more solid patterns of returns. Thus, the firms in the sample are required to have gone public before 2017, which results in six additional dual-class companies in the data set being excluded and the remaining 48 companies are used in the regression analysis.

3.2. The Matching Process

The 48 selected dual-class companies within the screened Technology sector are individually matched with 48 similar single-class companies within the same sector. The primary factor utilized in the matching process is the market capitalization as of 14 March, 2018. Every dual-

[7] Synonymously referred to as the "Technology sector" in remaining sections.

class company is assigned a relative spectrum above and below their current market capitalization, which is used to ensure that matching companies are in the same range of market value. The secondary factor is business similarity, where specific single-class companies are selected from the market capitalization spectrum based on their similarity to the dual-class firms' businesses. In other words, the matching process results in a set of 96 companies, containing 48 matched pairs primarily based on market values and business resemblances (see Table A5 in Appendix for a complete list of the matched companies). By matching the companies this way, industry- and value-related business cycles, as well as subsector specific news and regulations, are adjusted for to a greater extent.

Following the matching process, excess daily returns are computed for the 96 companies using the available share data for cash and price adjusted returns between 1 January, 2003, and 31 December, 2017 from CRSP.

4. Hypothesis Development

Looking at the related literature in relation to the defined data, a hypothesis can be developed. The general conception is that a dual-class structure enables managerial entrenchment (Gompers et al., 2003) and reduces overall firm value from a financial performance perspective (Masulis et al., 2009).

The consequence of reduced financial performance should be negative abnormal returns, given it has not been fully incorporated into the pricing of dual-class securities, as proposed by Gompers et al. (2009). However, there could be reputational constraints on potential agency costs (Bebchuck et al., 2000) and even potential benefits of a dual-class structure from a governance perspective. As the Technology sector has a demand for strong innovation and quick adoption, divergence between cash flow rights and voting rights may be of benefit for productive narcissists in key management positions. If true, the relationship between share class-structure and performance could be the opposite and even generate positive abnormal returns if dual-class firms are undervalued due to the risk of managerial entrenchment and agency costs. When matching dual-class companies with single-class equivalents, there is even some support for dual-class firms outperforming in terms of stock-market returns and accounting measures of firm performance (Böhmer et al., 2009). Could a consequence be that dual-class structures may be more appropriate in certain industries or parts of business cycles?

The mixed results for performance of dual-class firms makes it plausible to suspect a greater spread in performance between dual-class firms compared to single-class equivalents. A constructed dual-class portfolio should thereby most likely vary more in regression characteristics over time compared to a single-class portfolio.

In summary, mixed previous research regarding dual-class share performance could be a sign that the effect is contextual. Mixed results make it difficult to state any clear hypothesis regarding abnormal returns, but greater company control for management could be beneficial in certain environments and make it possible to more efficiently run a company. Fundamental firm value and performance should be reflected in the share performance and, if not fully incorporated in the share price, differences in ownership structures for firms in the Technology sector could be used to construct a favourable trading strategy.

Hypothesis: *The potential risks and benefits of a separation between cash-flow rights and voting rights create greater divergence in stock performance characteristics for dual-class firms, both across firms and over time. Differences in stock performance compared to single-class companies should make it possible to exploit abnormal returns in the Technology sector.*

5. Methodology

5.1. Overview

In order to compare performance between single- and dual-class companies within the Technology sector, an asset pricing study is conducted. Due to the Information Technology bubble ("dot-com bubble") during the early 2000's, the time horizon for the study starts in 2003 in order to reduce effects due to noise traders, herding and speculative behaviour that may have resulted in large mispricings. The choice of time frame thus mitigates the risk of inaccurate results due to excess irrational market behaviour reflected in the data set. The study is divided into three sections:

I. Describing the average regression results for the selected companies and their respective portfolios (dual-class versus non-dual-class), annually and over the entire time horizon (2003-2017).

II. Comparing the development of annual performance and regression characteristics of the dual-class company portfolio in relation to the matched single-class portfolio over the first ten years (2003-2012).

III. Formulating and testing a trading strategy for the last five years (2013-2017) based on the differences in regression characteristics identified in the second section.

The first section (I) compares the average characteristics of the companies in the two different share class structures over the entire time frame (2003-2017). Initially, regression characteristics of two constructed portfolios are compared. One portfolio includes the dual-class companies and the other portfolio includes the single-class equivalents. An equal-weighted portfolio approach is chosen in order to avoid firms with large market capitalizations dominating the portfolio performances. Based on the matching process of companies, both portfolios should at the same time have similar average market capitalizations in the equal-weighted approach. Daily excess returns are used to calculate annual variable coefficients between 2003 and 2017. The coefficients are based on the Carhart four-factor model (see Section 5.2 and Equation 1). The portfolios are updated as new firms enter the market in order to include stocks in the data set that go public throughout the time horizon. However, new stocks are not included until after the 20th day of trading in order to adjust for the phenomenon of underpricing of initial public offerings as discussed by Ritter (1991). When more stocks in the data set are included in the portfolios over time, the portfolios become more diversified. Based on the yielded annual regression coefficients, it is possible to analyse average values as well as variations in the coefficient values between the two portfolio types. Potential differences can furthermore be examined in greater detail by comparing the two firm types based on individual coefficient values for each of the 96 firms over the entire time period (2003-2017). By doing so, one assumes the independent variable coefficients to be persistent over time and that larger time series data gives a better indication of the actual value. After computing these coefficient values for each selected company during the time horizon, descriptive statistics are calculated for the dual-class companies and compared to the statistics of the single-class companies. These findings are used to provide further explanations to the findings in the second and third section.

In the second section (II), the development of the two constructed portfolios (described in the previous paragraph) and their yearly regression coefficients are analysed between 2003 and 2012. Calculating yearly coefficients and updating the portfolios, with adjustments for potential underpricing of IPOs, makes it possible to examine how ownership structure affects securities' regression characteristics over time. Comparison of the separate portfolios over time also highlights differences between the portfolio types as if they were two different indices where the significant difference is the ownership structure.

In the third section (III), patterns from the second section are analysed in order to identify a trading strategy. The strategy is to be based on differences between the two portfolios and is tested for the last five years of data (2013-2017). The strategy aims to address if findings from the second section can be used to generate abnormal returns that either oppose or support previous research regarding dual-class firms.

The methodology and independent variables have been carefully chosen to be able to explain share performance as exhaustively as possible. It is important to emphasize that one fundamental assumption is necessary in order to increase the explanatory ability of the results. Because returns are calculated without adjustment for costs incurred from brokers and clearing houses, trading costs are omitted and assumed to have little effect on the results.

5.2. Choice of Regression

The independent variables in the excess return regressions consist of the three Fama-French factors as well as the momentum factor. The Fama-French benchmark factors are chosen as they have been commonly identified as risk factors in returns on stocks (Fama and French, 1993). The three factors are formed from size/book-to-market without hold ranges and transaction costs. Combining the momentum effect with the Fama-French factors creates a model, the Carhart four-factor model, which is considered to explain the persistence in funds' mean and risk-adjusted returns (Carhart, 1997).

The factors above are chosen in order to adjust for fundamental anomalies beyond the traditional Capital Asset Pricing Model and create a multifactor asset-pricing model that serves to exhaustively describe potential drivers of returns. All factors are downloaded from the data library of Kenneth R. French that bases the values on CRSP data. The following variable descriptions are based on the definitions from the data library.

The first factor, RMRF, is the excess returns of the market portfolio. It is constructed by value-weighting returns on all stocks listed on NYSE, AMEX, and NASDAQ and subtracting the daily risk-free factor derived from the one month Treasury bill rate[8].

The second factor, SMB (Small Minus Big), composes of the average returns of three small-cap portfolios: one value, one neutral and one growth portfolio, minus the average returns of three large-cap portfolios, with the same classifications as the small-cap portfolios.

The third factor, HML (High Minus Low), is formed by taking the average returns of two value portfolios: one small value and one big value, and subtracting the average returns of two growth portfolios: one small growth and one big growth.

The fourth factor, UMD (Momentum), is constructed by taking the average returns of two high prior return portfolios and subtracting the average returns of two low prior return portfolios.

The entire regression for excess returns, R_t, can be summarised as follows:

$$R_t = \alpha^{\mathrm{c}} + \beta_{\mathrm{MKT}} RMRF_t + \beta_{\mathrm{SMB}} SMB_t + \beta_{\mathrm{HML}} HML_t + \beta_{\mathrm{UMD}} UMD_t + \varepsilon_{\mathrm{t}} \quad (1)$$

The market coefficient, β_{MKT}, shows the securities' exposure to the market risk. As the coefficient increases in size, it shows a larger expected excess returns for the stock in relation to the market risk premium.

Historically, as small-cap stocks tend to outperform large-cap stocks according to Fama and French (1993), it means that if $\beta_{\mathrm{SMB}} > 0$, the portfolio or stock is of small-cap characteristic. On the contrary, if $\beta_{\mathrm{SMB}} < 0$, it suggests that the portfolio or stock is similar to large-cap stocks.

[8] From Ibbotson Associates.

Regarding HML, high book-to-market (high value) stocks tend to outperform low book-to-market stocks (growth stocks). Thus, if $\beta_{HML} > 0$, it means that the portfolio or individual stock has a high book-to-market ratio (which is the characteristic of value stocks), whereas if $\beta_{HML} < 0$, the portfolio or stock is a growth security.

The momentum beta displays the exposure to momentum effects. If $\beta_{UMD} > 0$, it means that portfolio returns are positively correlated with prior returns, whereas if $\beta_{UMD} < 0$, the portfolio has an inverse relationship with prior returns.

Based on the main regression using two different portfolios, heteroscedasticity can be tested for. By performing the Breusch-Pagan/Cook-Weisberg (B-P/C-W) Test, a null hypothesis of all error variances being equal can be tested against the alternative of error variances being dependent functions of one or more regression variables. Running the test on the regressions for the two portfolios between 2003 and 2017 shows the presence of heteroscedasticity for several years. The results for each individual year and portfolio are reported in Table A1 in Appendix. The B-P/C-W Test results for heteroscedasticity motivate the use of robust regressions in order to avoid biased standard errors for the coefficients, in accordance with OLS assumptions. As a consequence, all regressions are made to be robust in order to enable comparability and the adjustment serves a conservative measure to respond to the presence of heteroscedasticity.

To summarise, the methodology aims to examine and describe how dual- and single-class companies vary in performance during the selected time horizon. The three different sections in the methodology are intended to give a holistic description depending on if the coefficient variables are viewed to be constant or believed to change over time. Literature within traditional finance provide support for adding the chosen variables. Thus, it is reasonable to assume that anomalies captured through abnormal returns in the constant term of the regression[9] can relate to the difference in share class structures. If markets are informationally efficient it could further provide support for adding a share class component when calculating expected returns in order to price securities more accurately.

[9] The constant term of the regression is α^c (alpha) and can also be defined as the "constant coefficient".

6. Empirical Results

6.1. Descriptive Overview on a Portfolio- and Firm-specific Level

The results are divided into three sections, as explained in the methodology. From the beginning of 2003 to the end of 2017 there were 3,776 trading days that have been used in the results. As the data consists of 15 calendar years, there is an average of 251.7 trading days per year in the data.

Building up to the sections of comparison of portfolio performances and subsequent trading strategies for the second time horizon (2013-2017), descriptive statistics across the entire time horizon can be computed. The statistics can be presented both on a portfolio- as well as firm-specific level.

Table 2: Descriptive regression statistics for the dual-class portfolio

	RMRF	SMB	HML	UMD	CONS
Mean	1.048	0.645	-0.246	0.059	0.037
SD	0.184	0.278	0.281	0.224	0.063
IQR	0.166	0.292	0.328	0.322	0.069

Table 3: Descriptive regression statistics for the single-class portfolio

	RMRF	SMB	HML	UMD	CONS
Mean	1.071	0.647	-0.247	-0.039	0.027
SD	0.079	0.218	0.209	0.142	0.042
IQR	0.093	0.158	0.232	0.171	0.020

Notes: Tables 2 and 3 describe the mean, standard deviation (SD) and interquartile range (IQR) for the dual-class and single-class portfolios' regression coefficients. The interquartile range is calculated as the differences between the 75th and 25th percentile of coefficient values. The coefficients are calculated on an annual basis between 2003 and 2017, meaning that the descriptive statistics for each coefficient are based on 15 values.

Looking at the descriptive statistics above for the two portfolio types, it is evident that the dual-class portfolio has coefficients that vary to a greater extent compared to its single-class equivalent (based on standard deviations and interquartile ranges). Mean values do at the same time appear to be relatively similar between the portfolios. The result makes it interesting to further examine in detail the differences in performance between the individual firms in each portfolio to see if the differences also exist on a firm-specific level. Statistics for the performance of companies in each portfolio, based on individual regressions for all 96 companies from 2003 to 2017, are summarised below.

Table 4: Descriptive regression statistics for dual-class firms

	RMRF	SMB	HML	UMD	CONS
Mean	1.148	0.595	-0.433	0.028	0.030
SD	0.274	0.378	0.468	0.240	0.090
IQR	0.387	0.648	0.642	0.199	0.077
Min	0.660	-0.127	-1.435	-0.590	-0.323
Max	1.888	1.341	0.469	0.744	0.167

Table 5: Descriptive regression statistics for single-class firms

	RMRF	SMB	HML	UMD	CONS
Mean	1.095	0.629	-0.274	-0.037	0.032
SD	0.244	0.420	0.344	0.122	0.034
IQR	0.239	0.646	0.362	0.156	0.036
Min	0.290	-0.334	-1.176	-0.373	-0.048
Max	1.689	1.440	0.316	0.219	0.132

Notes: Tables 4 and 5 describe main regression statistics for the 48 dual- and 48 single-class firms respectively over the entire time period from the beginning of 2003 to the end of 2017. The average number of observations per dual-class firm was 1,742 observations, whereas the average per single-class firm was 3,182 observations. Mean is the average of each regression coefficient for each category of firms. SD is the standard deviation of each regression coefficient for each category of firms. IQR is the interquartile range, calculated as the differences between the 75th and 25th percentile. Min is the minimum value and Max is the maximum value.

Looking at the descriptive coefficient data above, the dual-class firms tend to have higher market betas and a greater spread between the values. The spread is furthermore greater for dual-class firms for the coefficients of HML and UMD as well as for the constant value, alpha (CONS). Both firm types have mean values of alpha that are close to each other. The coefficient of momentum is close to zero for both categories, but the mean is negative for single-class firms and positive for dual-class firms. For the coefficient of SMB, the single-class firms display a larger spread with more extreme values, but the interquartile distances are very similar for both firm types.

As three out of five regression coefficients appear to have mean values that are similar when comparing across both firm types, it is relevant to test for if coefficient differences between firm types are statistically significant. As the dual- and single-class firms have been matched, a Wilcoxon Signed Rank Test can be used to test the null hypothesis that coefficient differences between the two types of firms is centred around zero. As the test is nonparametric, less assumptions are required, but it is still necessary to assume that coefficient differences follow a symmetric distribution. For large samples (greater than 20), normal approximation can be used in the test. Results are summarised in Appendix (Table A4) and show that only the coefficients for HML and UMD are statistically significant (2.36% and 3.32% respectively). One can hereby not reject that the differences for the remaining three factors are distributed around 0. The findings are intuitively supported by Table 4 and Table 5 as these three factors have close values between the two firm types on average. Despite potentially having the same average values, it is evident that the spread for dual-class firms' regression results appears to vary in between firms to a greater extent compared to the single-class equivalents. Dual-class firms seem to have greater average exposure to market risk, lower book-to-market values (more growth firms) and less small-cap characteristics. However, it is hard to draw any major comparisons without taking the coefficients' significance levels into account. Tables 6 and 7 display the t-statistics for each coefficient, based on the average and median values.

Table 6: Dual-class firms' t-statistics of regression coefficients

	RMRF	SMB	HML	UMD	CONS
Mean	12.94	3.94	-2.11	0.11	0.58
Median	11.41	2.79	-2.54	0.12	0.65

Table 7: Single-class firms' t-statistics of regression coefficients

	RMRF	SMB	HML	UMD	CONS
Mean	22.71	6.31	-2.59	-0.65	0.80
Median	23.50	6.27	-2.67	-0.33	0.59

Notes: Tables 6 and 7 show the mean and median t-statistic values of the regression coefficients for the dual- and single-class firms over the entire time period (2003-2017). Both the mean and the median are based on 48 firms per table.

The mean and median significance levels show that the coefficients for RMRF, HML and SMB are on average significant. Thus, generally significant findings for the entire section are that the coefficients for RMRF and HML vary more for dual-class firms. The opposite is partially supported for SMB where single-class firms have greater standard deviation, but the interquartile range is marginally smaller. Out of the three significant coefficients, it is only possible to, based on the Wilcoxon Signed Rank Test, discard the possibility of the coefficient differences across the firm types being centred around zero for HML. Following these results, it is of interest to study the constructed portfolios' annual performances.

6.2. Portfolio Performances

Tables 8 and 9 summarise the annual regressions of the two equally weighted portfolios between 2003 and 2012. It is evident that the significance levels, based on two-sided t-tests, are at satisfactory levels for the coefficients regarding returns in relation to exposure to market risk and firm size. Market betas for the single- and dual-class portfolios are significant at the 0.1% level for every year in the regressions. Regarding book-to-market, HML coefficients for the single-class portfolio are significant for the years between 2004 and 2012, several at the 0.1% level. For the dual-class portfolio, HML coefficients are only significant for 2008 and 2011. The UMD coefficients for the dual-class portfolio are significant for the years 2007-2010, as well as 2012. Single-class UMD coefficients are significant for 7 out of 10 years, whereas 2004 and 2006-2007 are insignificant. Abnormal returns experience low t-statistics for both portfolios. Thus, in this section of the paper, we cannot draw any significant conclusions regarding portfolio differences in terms of book-to-market exposure, momentum effects and abnormal returns.

Table 8: Annual regression coefficients for the dual-class portfolio

	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012
RMRF	1.471***	1.348***	0.778***	0.960***	1.070***	0.970***	0.839***	0.941***	1.079***	0.920***
	(14.04)	(10.54)	(6.10)	(9.98)	(12.83)	(22.40)	(12.64)	(19.28)	(23.30)	(16.96)
SMB	1.305***	1.128***	0.902***	0.508***	0.397	0.399***	0.477***	0.472***	0.518***	0.724***
	(5.87)	(6.52)	(4.57)	(4.20)	(1.95)	(4.43)	(4.77)	(6.75)	(4.99)	(6.70)
HML	0.461	-0.509	-0.573	-0.499	-0.049	-0.191*	0.119	-0.147	-0.457***	-0.158
	(1.20)	(-1.55)	(-1.90)	(-1.86)	(-0.14)	(-2.06)	(1.67)	(-1.55)	(-4.04)	(-1.48)
UMD	0.067	-0.069	-0.054	0.215	0.555***	-0.159*	-0.117*	0.179*	-0.134	-0.209**
	(0.37)	(-0.28)	(-0.31)	(1.83)	(3.53)	(-2.10)	(-2.44)	(2.15)	(-1.61)	(-2.70)
CONS	0.185	-0.008	0.045	0.073	0.017	-0.042	0.139*	0.051	-0.002	-0.007
	(1.76)	(-0.12)	(0.76)	(1.50)	(0.28)	(-0.61)	(2.52)	(1.47)	(-0.04)	(-0.18)
N	252	252	252	251	251	253	252	252	252	250
R^2	0.526	0.612	0.440	0.627	0.640	0.851	0.808	0.840	0.896	0.738
adj. R^2	0.518	0.605	0.431	0.621	0.634	0.848	0.804	0.838	0.894	0.734

t statistics in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Notes: Annual robust regressions on dual-class portfolio returns in relation to excess market returns (RMRF beta), returns on small-cap portfolios in relation to large-cap portfolios (SMB beta), difference in returns between value and growth portfolios (HML beta) and average returns of high prior return portfolios minus average returns of low prior return portfolios (UMD beta). The constant value, alpha (CONS), is a result of the regression on the independent variables and N is the number of observations (trading days) for the dual-class portfolio per year.

Table 9: Annual regression coefficients for the single-class portfolio

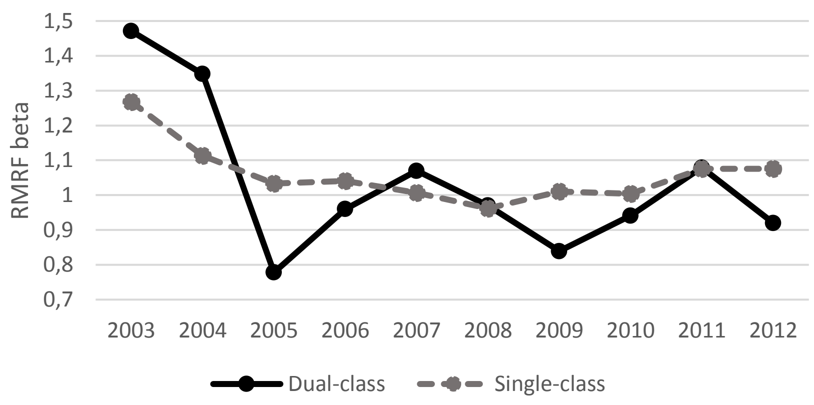
	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012
RMRF	1.268***	1.113***	1.033***	1.041***	1.007***	0.962***	1.010***	1.004***	1.076***	1.076***
	(24.20)	(15.49)	(16.65)	(18.02)	(29.55)	(31.73)	(22.20)	(25.74)	(30.51)	(24.02)
SMB	1.025***	1.192***	0.640***	0.812***	0.602***	0.488***	0.562***	0.558***	0.681***	0.623***
	(10.36)	(11.43)	(8.34)	(11.16)	(7.07)	(7.16)	(8.46)	(9.12)	(12.74)	(10.46)
HML	0.173	-0.335*	-0.372*	-0.464**	-0.533***	-0.157*	-0.155**	-0.233***	-0.441***	-0.403***
	(1.19)	(-2.27)	(-2.44)	(-2.69)	(-3.99)	(-2.36)	(-2.83)	(-3.71)	(-4.96)	(-3.81)
UMD	-0.202*	-0.0973	-0.184**	-0.0475	0.108	-0.118*	-0.0842*	0.146*	-0.121*	-0.251***
	(-1.98)	(-0.90)	(-2.72)	(-0.67)	(1.57)	(-2.44)	(-2.18)	(2.36)	(-2.48)	(-4.48)
CONS	0.0342	0.0212	0.0271	0.0378	0.0314	-0.0530	0.151***	0.0204	0.0136	0.0411
	(0.74)	(0.56)	(0.92)	(1.46)	(1.03)	(-1.14)	(3.81)	(0.75)	(0.48)	(1.56)
N	252	252	252	251	251	253	252	252	252	250
R^2	0.798	0.817	0.794	0.853	0.846	0.920	0.890	0.911	0.952	0.891
adj. R^2	0.794	0.814	0.791	0.851	0.843	0.919	0.889	0.910	0.951	0.889

t statistics in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Notes: Annual robust regressions on returns of the single-class portfolio in relation to excess market returns (RMRF beta), returns on small-cap portfolios in relation to large-cap portfolios (SMB beta), difference in returns between value and growth portfolios (HML beta) and average returns of high prior return portfolios minus average returns of low prior return portfolios (UMD beta). The constant value, alpha (CONS), is a result of the regression on the independent variables and N is the number of observations (trading days) for the single-class portfolio per year.

Based on Table 8 and Table 9, it is possible to plot and compare the significant results over time. Figures 2 and 3 illustrate the annual regression results for market beta and firm size beta for the two portfolios. These coefficients can be viewed as most relevant to study based on their significance levels.

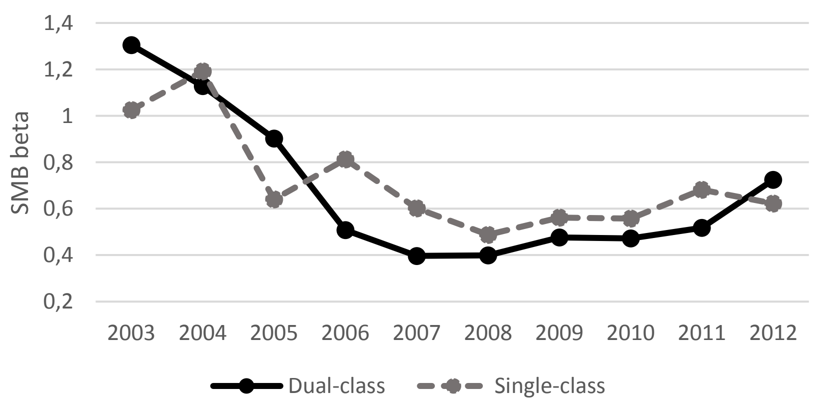
Figure 2: RMRF beta over time



Notes: Development of RMRF beta over time for the dual- and single-class portfolio. Values are based on the first row of regression coefficients in Table 8 and Table 9.

Figure 2 displays the values of the market beta for the two portfolios from 2003- 2012. The graph shows that the market beta for the dual-class portfolio changes frequently and has a higher amplitude, compared to the more stable single-class portfolio beta with values closer to a baseline around 1.05. The peaks for the dual-class portfolio's market beta occur during 2003, 2007 and 2011 whereas the valleys are in 2005, 2009 and 2012 (including end-points).

Figure 3: SMB beta over time



Notes: Development of SMB beta over time for the dual- and single-class portfolio. Values are based on the second row of regression coefficients in Table 8 and Table 9.

Figure 3 shows the values of the SMB beta for the two portfolios between 2003 and 2012. The dual-class portfolio seems to change in a more predictable manor compared to the single-class portfolio. The single-class portfolio does at the same time appear to vary less across its average value. The peaks for the dual-class portfolio are the two end-points, whereas the valley is between 2007 and 2008.

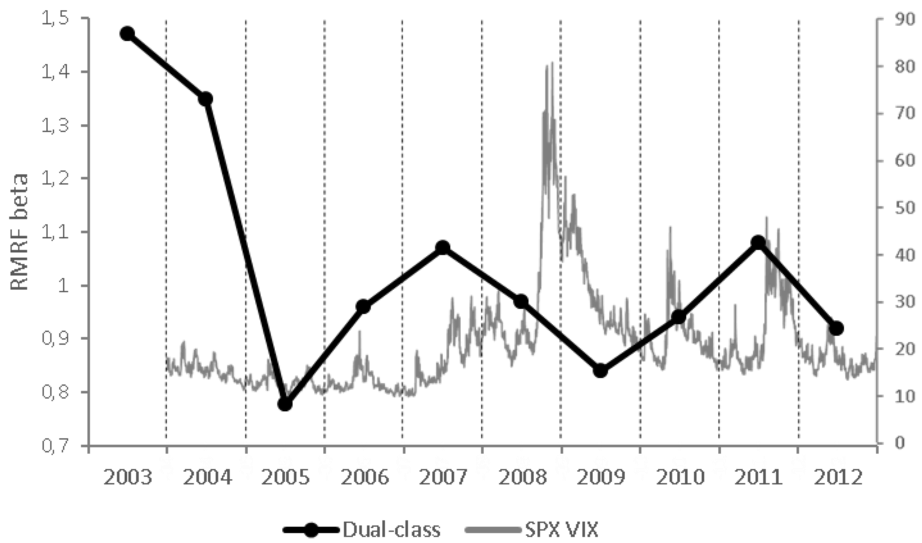
The coefficients for HML, UMD and abnormal returns were overall insignificant. However, it is still relevant to comment on the characteristics (brief descriptions can be found below and see Appendix for figures, Figure A1, A2 and A3). Similar to the market beta, the single-class portfolio HML coefficient value is more stable over time compared to the dual-class equivalent. The dual-class portfolio has a larger spread of HML beta with more peaks and valleys relative to the single-class portfolio. Both portfolios follow a similar pattern for momentum beta with small value differences between 2008 and 2012. The dual-class portfolio experiences a relatively higher peak for 2007. An additional observable characteristic is that the portfolio momentum betas move in opposite directions between 2003 and 2005. The peak value for the dual-class portfolio's abnormal returns occurred in 2003 and is higher than the single-class peak of 2009. Simultaneously, the single-class portfolio clearly shows a smaller deviation of abnormal returns between 2003 and 2007.

6.3. Trading Strategy

Based on the findings in 6.2 regarding the annual data for the portfolios' market betas, it is possible to devise a trading strategy. The coefficients for exposure to market risk have the highest t-statistics, and vary to a greater extent for the dual-class portfolio. Looking back at Figure 2, the dual-class market beta peaks during 2003, 2007 and 2011. 2003 was a year of strong growth for technology stocks following the end of the dot-com bubble (*Morningstar*, 2004), whereas early 2007 is regarded to have been a build-up market before the start of the U.S. financial crisis (*OECD*, 2007). It was also in the third quarter of 2011 that stock markets experienced a drop due to the European sovereign debt crisis. Analysing the valleys, it is possible to conclude that the low dual-class market beta values in 2005 and 2009 correspond to downturns following hurricane disasters in the U.S. during 2005 and the deep recession following the financial crisis in 2008. The data in relation to real-time events suggests that the exposure to market risk for the dual-class portfolio is to a greater extent dependent on the overall situation in the financial markets compared to its single-class equivalent. More stable market conditions seems to correspond with a higher market beta for the dual-class portfolio and adversely, more volatile market performance appears to lead to a lower market beta. In order to further examine the relationship between performance and the portfolios' exposure to market risk, a volatility index can be used as a proxy for the effect of real-time events and perceived risk in the market.

The SPX VIX (hereafter referred to as "VIX") is an index provided by the Chicago Board Options Exchange and is based on the implied volatility of 30-day options on the S&P 500. It is available from 2004[10] and constructed based on calculations for a risk-neutral cumulative variance of the market. During stable market conditions the VIX stays below 20, whereas during the peak of the U.S. financial crisis in 2008 it reached 80 and during mid 2011 it spiked over 45 due to the European sovereign debt crisis. As the VIX shows implied volatility, it can be viewed as the market sentiment regarding forward looking systematic risk. The figure below combines Figure 2 with the daily closing price of the VIX between 2003 and 2012.

Figure 4: RMRF beta combined with VIX



Notes: Development of market beta over time for the dual-class portfolio combined with SPX VIX. VIX-values are displayed on the secondary Y-axis.

When comparing the VIX with the results from the change of market beta over time, there is evidence that the dual-class portfolio displays lower market betas in times of recently high market volatility. As market volatility is low, the market beta adversely tends to be high. An example is late 2008 when the market volatility was high, which was followed by a lower value for the market beta in 2009. The outcome is that during times of low systematic risk, the dual-class portfolio covaries with the market's returns to a greater extent compared to when

[10] Index calculation methodology was updated 22 September, 2003.

there is evidence for high levels of systematic risk. The findings make it interesting to explore if it could be possible to form a trading strategy based on market volatility. The inverse movement tendencies of market beta for the dual-class portfolio in relation to implied market volatility, makes it plausible to suspect that other regression characteristics for the dual-class firms also change depending on market volatility. Thus, two trading strategies based on market volatility can be tested and compared.

1. Establish a long position in the dual-class portfolio during times of low market volatility, i.e. relatively stable general market conditions. The benchmark VIX-value used to indicate lower volatility is below or equal to the relative measure of 1. Once the market volatility increases beyond the relative measure of 1, exit the dual-class position and go long in the single-class portfolio instead.

2. Establish a long position in the dual-class portfolio during times of higher market volatility, i.e. relatively unstable general market conditions. The benchmark VIX-value used to indicate higher volatility is above the relative measure of 1. Once the market volatility decreases below the relative measure of 1, exit the dual-class position and go long in the single-class portfolio instead.

The measure for the relative level of volatility is constructed based on the closing price of the VIX from the previous day in relation to the average from the past three years (assuming an average of 252 trading days per year). It can be summarised as per below, where *j* is a specific day for deciding which portfolio to enter a long position in.

$$\frac{VIX_{j-1}}{\left(\frac{\sum_{i=j-1-252*3}^{j-2} VIX_i}{252*3}\right)} \qquad (2)$$

Past values can hereby be used as a signal for choice of which portfolio to go long during a certain day. A relative measure makes it possible to formulate a trading strategy based on current volatility in relation to how risk has been perceived during recent years. By using the relative measure, a value above 1 will show high implied volatility in relation to the past three years. A value of 1 or below is equal to low relative volatility as the average is equal to or higher than the current volatility. As the relative VIX-measure is constructed with a start on the first day of trading in the trading strategy period (beginning of 2013), the strategy returns commence from the second day of trading (the choice of portfolio to go long requires the relative VIX-measure from the previous day). The choice of a three-year average is based on the fact that short-run macroeconomic deviations from predicted growth as if no economic shocks were present are believed to last for at least two years (Jones, 2018).

Going long only in the trading strategy can be motivated from two aspects: comparability and potential co-movement of the single- and dual-class portfolios. Solely going long makes it possible to clearly compare the performance of the strategies with that of the individual performance of the dual-class and single-class portfolios over the test period from 2013-2017. The long-only approach further relates to and makes it possible to comment on the results in relation to the findings of Gompers et al. (2009), who regress returns on portfolios based on share class. From the co-movement perspective, a majority of the figures from Section 6.2 indicate positive co-movement between the two portfolios' coefficients. Simultaneously going short the opposing portfolio as we long a portfolio will thereby most likely give low coefficient levels as well as low values of the coefficient of determination and, if positive co-movement is strong, reduce the size of potential abnormal returns.

Table 10: Performance of trading strategies between 2013 and 2017

	Strategy 1	**Strategy 2**	**Dual-class**	**Single-class**
RMRF	1.119****	1.079****	1.101****	1.097****
	(55.92)	(46.84)	(42.92)	(67.62)
SMB	0.591****	0.524****	0.615****	0.500****
	(17.02)	(17.32)	(15.86)	(20.20)
HML	-0.311****	-0.238****	-0.346****	-0.202****
	(-6.79)	(-5.62)	(-6.98)	(-5.49)
UMD	0.0498*	0.00275	0.0286	0.0239
	(1.86)	(0.12)	(0.98)	(1.22)
CONS	0.0303*	0.00848	0.0234	0.0154
	(1.92)	(0.67)	(1.38)	(1.40)
N	1258	1258	1258	1258
$\boldsymbol{R^2}$	0.761	0.817	0.734	0.854
adj. $\boldsymbol{R^2}$	0.760	0.816	0.733	0.854

t statistics in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$, **** $p < 0.001$

Notes: Regression characteristics of proposed trading strategies in relation to the dual- and single-class portfolios from 2013 to 2017. N is the number of trading days, including all trading days for the time period except for the first day of trading in 2013 that is used for signaling in the trading strategies (see page 25).

Looking at the results displayed in Table 10, it is evident that the first strategy experiences higher abnormal returns, with 0.0303 compared to 0.00848, as well as a higher corresponding significance level, where Strategy 1 displays a t-statistic of 1.92 compared to 0.67 for Strategy 2. The coefficients for RMRF, SMB and HML are all significant for both strategies on a 0.1% level. The t-statistic for the UMD coefficient is higher for Strategy 1, with a value of 1.86 compared to 0.12 for Strategy 2. Based on these results, it is clear that Strategy 1 is the optimal choice of the two strategies. It is further noteworthy that Strategy 1 outperforms the dual-class and single-class portfolios' individual abnormal returns during the time period.

Besides looking at risk-adjusted excess returns (based on the Carhart four-factor model), a non-risk-adjusted approach can be used for "raw" excess returns beyond the risk-free rate.

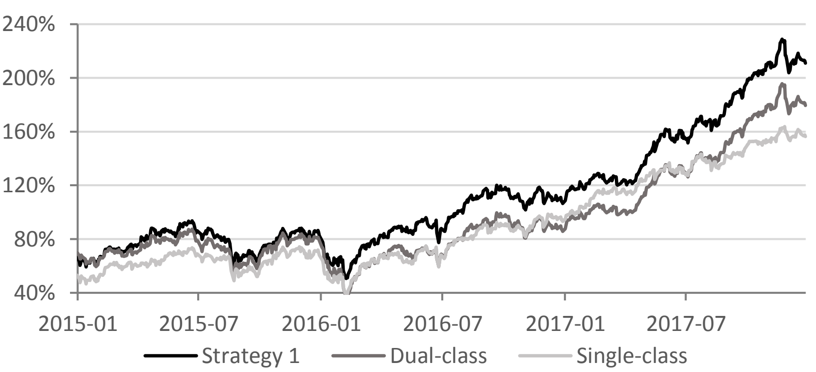
Table 11: Non-risk-adjusted annual excess returns

	Strategy 1	**Strategy 2**	**Dual-class**	**Single-class**
Excess Returns	25.5%	18.2%	22.8%	20.7%

Notes: Average annual non-risk-adjusted excess returns of proposed trading strategies in relation to the dual- and single-class portfolios from 2013 to 2017. Returns are calculated based on compounding of daily returns subtracted with the risk-free rate.

The non-risk-adjusted excess returns show that Strategy 1 outperforms both Strategy 2 as well as the dual- and single-class portfolios over the entire time period with a total five-year return of 210.9%. It can further be of interest to see how total period returns develop over the last three years where the returns differ to a greater extent between the strategies and portfolios. As Strategy 2 yields the lowest cumulative non-risk adjusted excess returns and has the lowest abnormal returns in the risk-adjusted approach, it is excluded in the figure below.

Figure 5: Non-risk-adjusted excess returns over time



Notes: Cumulative non-risk-adjusted excess returns from 2015-2017. Return percentages are based on beginning of 2013 as starting point.

Looking at Figure 5, Strategy 1 appears to have the highest cumulative non-risk-adjusted excess returns from 2015-2017, which further supports it being a beneficial strategy.

7. Discussion

Comparing the average regression results for the selected single- and dual-class companies over the entire time horizon, it is clear that differences exist. In the tables exhibiting descriptive statistics (Tables 2, 3, 4 and 5), a persistent pattern is displayed of dual-class firms having higher spread in regression characteristics. The finding is further supported in Section 6.2 as the annual regression coefficients for the dual-class portfolio on average vary more than the single-class equivalents.

Although the number of observations for each portfolio is large, there is a distinct difference between the average number of observations per dual-class firm, and the average number of observations per single-class firm. The difference stems from the fact that several included dual-class companies completed initial public offerings during, or in later stages of the analysed time horizon. This could partly explain the higher standard deviations for the dual-class portfolio's firms compared to the single-class portfolio's firms. However, as both average observation sizes are large and IPO underpricing is adjusted for to a certain extent, the standard deviations should still serve as sufficient estimates.

For the two constructed portfolios, there is no support for significant abnormal returns during the entire time period 2003-2017, both when looking annually as well as for the entire time period. Gompers et al. (2009) provide possible explanations to why there are no clear return patterns related to the dual-class structure, including but not limited to, the fact that the dual-class feature might be fully incorporated into stock prices. This could partly explain the similarities in abnormal returns between single- and dual-class portfolios in our data set.

When taking the variation for the statistically most significant measure, market beta, into account, a trading strategy can be constructed. Strategy 1 provides the largest and most significant abnormal returns, and only goes long dual-class firms during times of low relative market volatility and long single-class in times of high relative market volatility. Using a relative measure makes it possible to account for risk being perceived in relation to recent (three-year) market performance. The strategy goes long the dual-class portfolio when it is believed to have a high market beta (as illustrated in Figure 4) and long the single-class portfolio (that is believed to have a more stable beta) when the dual-class market beta is believed to be low. This pattern of varying betas is supported with the regression results in Table 10 where the RMRF coefficient is largest for Strategy 1, both compared to Strategy 2 as well as to the respective dual- and single-class portfolios alone. Furthermore, the non-risk-adjusted cumulative excess returns are larger for Strategy 1 compared to the two portfolios, which provides further support of its favourability. There may be two intuitive explanations for the findings above and the yield of larger risk-adjusted abnormal returns.

From a corporate governance and behavioural perspective, a plausible reason could be that investors tend to shy away from stocks that restrict shareholder rights to a greater extent during bearish times of higher volatility. The changes in demand could mean that these stocks are traded more frequently during more stable market conditions. Increased trading volumes could increase the amount of speculative behaviour in these stocks and make stock returns covary greater with market returns. As demand increases, investors may be willing to further discount the potential agency costs of a controlling-minority structure as discussed by Bebchuck et al. (2002), which could yield a greater alpha. If the market is believed to be inefficient, the abnormal returns could be created through behavioural aspects such as herding behaviour that makes new investors overlook the "correct" price that incorporates all available information.

An alternative explanation, if believing the market to be efficient, is that dual-class firms exhibit a kind of characteristic that yields higher returns during stable market conditions. The characteristic could relate to dual-class firm structures affecting intrinsic firm performance depending on market conditions. Returns should according to this view be purely based on risk and perhaps a controlling-minority structure affects a fundamental performance factor that increases risk during stable market conditions. As the perceived risk increases, so should also abnormal returns in the used model if not incorporating the additional risk factor.

In this paper, the included independent regression variables are the three benchmark Fama-French factors and the momentum factor, together forming the Carhart four-factor model (Carhart, 1997). The reasoning for selected independent variables was mainly based on the factors' applicability and explanatory power regarding stock returns. We do not exclude the possibility that there may be omitted variables in our model. This could be a range of different factors, such as cyclical effects or sub-industry-specific drivers of return related to the business nature of different technology firms. In addition, there may be more diffuse omitted variables linked to governance, corporate culture and management rationale, as expressed by Paul Gompers et al. (2003). The management features are more difficult for investors to incorporate into stock prices, and as mentioned earlier, it might be the case that the business nature within the Technology sector creates a more suitable environment for insider control structures relative to other industries. This may partly explain differences in results from studies that are not industry-specific, such as the paper by Bebchuk et al. (2008).

Previous research on the impact of dual-class structures lacks isolation and focus on specific industries. The general academic consensus is that dual-class structures are negative for shareholder value and performance, but could it be the case that the controversial feature is actually a good fit for certain industries? The innovative nature and fast-paced environment within the Technology sector requires innovative management with long-term visions. Tech-entrepreneurs that risk losing control of their visions may be discouraged to go public, and thus deny investors access to important companies of the future. There is no doubt that dual-class structures can increase agency problems and decrease firm value, as argued by Masulis et al- (2009) and Bebchuk et al. (2008). However, there is also no doubt regarding the increasing popularity, high investor demand and regulatory changes in favour of dual-class structures. There is not sufficient evidence to conclude that dual-class structures are always negative for outside shareholders and based on results in this paper and papers such as Böhmer et al. (1995), industry-specific factors should most likely have strong influence on dual-class firms' share performance.

Looking from a more general perspective the results are dependent on the perceived causality of the methodology. It could be viewed that the findings arise from isolating the general dual-class component by removing industry-specific effects. Adversely, one may argue that the findings are specific for dual-class firms in the Technology sector. In terms of industry age and business maturity, the Technology industry can be regarded as standing out from more traditional industries due to its relatively young age and containment of many firms with growth characteristics. Undoubtedly, there may be subsector differences and exceptions to this claim, however, the results in this paper support the idea that the firms in the data set belong to a growing industry. This is reflected through the positive SMB coefficients and negative HML coefficients on a portfolio- as well as firm-specific level in the results. Regardless of perspective, it is at least evident that the findings exist in the studied sector.

To summarise, the specific focus on securities within the Technology sector could partly explain that dual-class firms performed relatively on par with single-class equivalents. The dual-class feature may be more suitable within the Technology industry compared to other industries. Despite expressing concerns regarding the equity structure, it is evident that investors want to participate in the many technology dual-class offerings.

8. Conclusion and Remarks

8.1. Conclusion

The dual-class structure is a highly debated and relevant topic in today's business environment. The general academic consensus is that dual-class structures are associated with increased agency costs, decreased shareholder value and sub-optimal stock performance, compared to the traditional single-class structure. This thesis stands out from other related literature because of the niche intra-industry analysis of dual-class stock performance, with a focus on the U.S. Technology sector. It is an industry where dual-class listings are becoming increasingly popular, and thus it is particularly interesting to examine.

In line with the hypothesis, the time-varying regressions yield a larger spread for the dual-class regression coefficients and a greater divergence in stock performance characteristics, in contrast to the more stable single-class equivalents. The measured abnormal returns for the individual portfolios are similar albeit the t-statistics are low. It is thus not plausible to conclude any differences in abnormal returns when solely comparing dual-class firms to their single-class equivalents. Insignificant differences in abnormal returns is further in line with the findings of Gompers et al. (2009) who use the same regression model.

When constructing a trading strategy based on the statistically significant market risk coefficients, significant abnormal returns can be yielded at a significance level of 10%. This strategy builds on the trend mechanism of the dual-class portfolio's exposure to market risk. Using a relative VIX-measurement as an indicator of overall market volatility, one can observe and use the fact that dual-class stocks' returns tend to covary with the markets to a greater extent during times of low volatility compared to when volatility is relatively higher. As abnormal returns in the strategy are greater and more significant compared to the single-class and dual-class portfolios alone during the time period, it appears to be more successful than investing solely in one of the constructed portfolios. Depending on the view of prevalent market efficiency, the driver of the abnormal returns in the strategy with respect to dual-class shares can be interpreted differently. At the same time, the possibility of potentially omitted variables with explanatory power expressed through the current abnormal returns cannot be dismissed.

The findings in this thesis are based on a methodology that has intended to use academically justified empirical factors within the field of asset pricing to assess the performance of dual-class shares in relation to single-class equivalents. Our findings show that there is not sufficient evidence to conclude that dual-class structures are always negative for outside shareholders, and one can argue that industry-specific factors are likely to be important pieces of the dual-class performance puzzle.

8.2. Remarks and Further Research

Following the discussion of potential variable omittance, an interesting development in the conducted research could be to include a liquidity factor. An example would be to include the traded liquidity factor developed by Pástor and Stambaugh. The liquidity factor describes temporary price changes and returns accompanying order flow. Higher order flow is assumed to generate greater compensation and Pástor and Stambaugh find that expected returns for stocks on the NYSE and AMEX are related cross-sectionally to sensitivities of stock returns to innovations in aggregate liquidity. Stocks with higher sensitivity to aggregate liquidity are found to have substantially higher expected returns (Pástor and Stambaugh, 2003). Thus, it could be interesting to include a liquidity factor in a future asset pricing study.

Looking at our conducted methodology, it may be possible that some of the liquidity is reflected in momentum as previous returns affect the current demand. As the traded liquidity factor is estimated on a monthly basis and our research used daily excess returns, including the additional factor would either require data to be on a monthly basis or a unique daily liquidity factor must be constructed. Using monthly data would require a longer time horizon in order to reach satisfying significance levels in the regressions. Doing so by including years before 2003 would risk biased results due to the abundance of dual-class firms on the stock market, as well as the large speculative behaviours and time-specific effect during the dot-com bubble, which may be difficult to efficiently control for.

Relating to the results from the trading strategy, a larger set of firms and longer time horizon would be of interest to study the pattern in further detail. An alternative could be to identify additional technology stocks that exist in markets similar to the U.S. and also allow for dual-class share structures. Another suggestion could be to include multiple industries and try to control for industry-specific effects. Looking at additional industries beyond the Technology sector would also enable to elaborate the discussion following the results in this paper and examine the performance variation for dual-class structures across different industries.

Overall, the regressions are based on academically proven research. At the same time, potential risks that may affect the result have been mitigated by controlling for phenomena such as heteroscedasticity, IPO underpricing and speculative market bubbles. The paper builds on previous empirical findings and serves to provide explanations for dual-class shares' performance from an asset pricing perspective.

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Appendix

Table A1: Breusch-Pagan/Cook-Weisberg (B-P/C-W) Test

Year	**Dual-class**		**Single-class**	
	$\chi^2(4)$	**Prob.>**	**$\chi^2(4)$**	**Prob.>**
2003	17.71	0.0014	0.99	0.9117
2004	38.62	0.0000	2.85	0.5836
2005	7.94	0.0936	10.12	0.0384
2006	1.45	0.8351	23.13	0.0001
2007	16.69	0.0022	5.6	0.2307
2008	14.84	0.0051	12.21	0.0158
2009	12.56	0.0137	14.46	0.0060
2010	3.58	0.4665	3.72	0.4457
2011	22.89	0.0001	42.62	0.0000
2012	5.55	0.2354	26.12	0.0000
2013	3.09	0.5427	3.25	0.5171
2014	5.66	0.2260	13.37	0.0096
2015	2.56	0.6341	10.73	0.0297
2016	37.5	0.0000	27.64	0.0000
2017	40.14	0.0000	7.08	0.1316

Notes: Heteroscedasticity test of the null hypothesis of equal error variances (homoscedasticity) for every year between 2003 and 2017. The four degrees of freedom are a result of the number of independent variables in the non-robust regression. Prob. displays the significance level for each year and portfolio.

Table A2: Individual regression coefficients for dual-class firms

	RMRF		SMB		HML		UMD		CONS		N	adj. R2
d1	1.019***	(30.51)	-0.111	(-1.92)	-0.294***	(-4.08)	0.070	(1.80)	0.062*	(2.29)	3345	0.343
d2	1.081***	(14.97)	0.168	(1.58)	-0.662***	(-4.83)	0.463***	(5.28)	0.081	(1.49)	1393	0.185
d3	1.058***	(11.35)	0.236	(1.46)	-0.678***	(-4.36)	-0.019	(-0.18)	0.041	(0.68)	806	0.225
d4	0.974***	(22.15)	-0.122	(-1.60)	-0.018	(-0.22)	-0.003	(-0.07)	0.055	(1.92)	2444	0.428
d5	1.144***	(26.92)	-0.127	(-1.56)	-0.059	(-0.77)	0.012	(0.23)	0.096**	(3.06)	2900	0.403
d6	1.391***	(21.14)	0.191	(1.46)	-0.604***	(-4.42)	0.002	(0.03)	0.103*	(2.06)	3102	0.249
d7	1.160***	(17.13)	0.427***	(3.64)	-0.381**	(-3.11)	-0.052	(-0.77)	0.010	(0.21)	2594	0.265
d8	1.369***	(13.55)	0.502***	(3.88)	-1.076***	(-7.45)	-0.029	(-0.34)	0.00	(0)	1291	0.289
d9	1.426***	(8.41)	0.497*	(2.44)	-1.036***	(-4.62)	-0.230	(-1.49)	0.162	(1.57)	913	0.150
d10	1.176***	(6.12)	0.392	(1.52)	-0.602*	(-2.52)	-0.161	(-0.81)	0.167	(1.41)	511	0.102
d11	1.025***	(7.14)	0.084	(0.54)	-0.491**	(-3.08)	0.517**	(3.18)	0.087	(1.40)	311	0.275
d12	1.444***	(11.68)	0.290	(1.14)	-1.375***	(-5.35)	-0.307	(-1.75)	0.156	(1.40)	638	0.198
d13	1.584***	(9.90)	0.281	(1.52)	-0.259	(-1.39)	-0.183	(-1.43)	-0.085	(-1.00)	536	0.275
d14	1.462***	(6.47)	0.074	(0.31)	-1.105***	(-4.19)	-0.087	(-0.45)	0.032	(0.30)	497	0.176
d15	1.491***	(18.47)	0.195	(1.35)	-0.600***	(-4.22)	-0.465***	(-4.64)	-0.032	(-0.53)	1642	0.267
d16	0.867***	(18.94)	0.206**	(2.59)	-0.241***	(-3.38)	0.030	(0.77)	0.025	(0.94)	3776	0.262
d17	1.212***	(7.36)	0.585*	(2.51)	-0.505*	(-2.55)	0.406*	(2.26)	0.116	(1.10)	511	0.143
d18	1.155***	(9.43)	0.518*	(2.27)	-1.008***	(-4.54)	-0.111	(-0.75)	0.079	(0.78)	1028	0.105
d19	1.097***	(11.47)	0.847***	(5.44)	-0.334*	(-2.03)	0.143	(1.37)	0.078	(1.10)	1603	0.144
d20	1.329***	(21.88)	0.451***	(4.35)	-0.618***	(-5.15)	-0.178*	(-2.49)	0.075	(1.48)	3776	0.202
d21	1.888***	(3.40)	1.031*	(2.29)	-1.225**	(-2.85)	0.058	(0.14)	0.016	(0.08)	294	0.102
d22	1.260***	(10.24)	1.068***	(5.39)	-0.360	(-1.62)	0.182	(1.36)	0.146	(1.57)	1265	0.121
d23	1.547***	(10.01)	0.931***	(5.22)	-1.150***	(-3.61)	0.098	(0.88)	-0.015	(-0.18)	1144	0.241
d24	0.827***	(19.48)	0.465***	(5.81)	-0.029	(-0.36)	-0.057	(-1.12)	0.022	(0.64)	3219	0.230
d25	0.722***	(13.75)	0.342***	(4.31)	0.075	(0.79)	0.069	(1.22)	0.060	(1.59)	1771	0.182
d26	0.772***	(14.38)	0.493***	(5.42)	-0.061	(-0.68)	-0.067	(-1.33)	0.010	(0.29)	2497	0.303
d27	1.289***	(13.99)	1.341***	(9.01)	-0.894***	(-5.49)	0.010	(0.10)	0.069	(1.00)	1052	0.290
d28	1.160***	(5.85)	0.274	(1.06)	-0.203	(-0.72)	0.009	(0.05)	-0.034	(-0.27)	542	0.078
d29	1.167**	(2.76)	1.129**	(2.80)	-0.764**	(-2.81)	0.395	(1.40)	-0.165	(-0.94)	363	0.081
d30	0.752***	(6.12)	0.771***	(3.89)	-0.338	(-1.87)	0.019	(0.15)	-0.039	(-0.48)	1498	0.057
d31	1.409***	(21.60)	0.692***	(5.98)	-0.051	(-0.48)	-0.099	(-1.94)	-0.015	(-0.47)	3776	0.461
d32	1.239***	(9.09)	0.713***	(3.76)	-0.281	(-1.45)	-0.166	(-1.10)	0.002	(0.02)	720	0.191
d33	1.452**	(2.74)	0.951	(1.77)	-1.435***	(-3.86)	0.497	(1.64)	0.134	(0.65)	301	0.111
d34	0.785***	(20.20)	0.834***	(11.64)	-0.037	(-0.44)	0.032	(0.64)	0.013	(0.39)	3776	0.222
d35	1.364***	(12.05)	0.535**	(2.77)	-0.681**	(-3.19)	-0.162	(-1.24)	0.036	(0.42)	1814	0.126
d36	0.741***	(4.16)	0.599*	(2.40)	-0.257	(-1.09)	-0.033	(-0.19)	0.157	(1.44)	618	0.062
d37	1.148***	(28.6)	0.684***	(9.17)	-0.530***	(-5.12)	0.010	(0.16)	0.039	(1.00)	3776	0.251
d38	1.240***	(10.94)	0.474**	(2.59)	-0.186	(-0.95)	0.172	(1.33)	0.057	(0.76)	1117	0.147

d39	1.447***	(7.23)	0.814**	(2.81)	-0.801*	(-2.37)	-0.590*	(-2.55)	-0.323*	(-2.25)	619	0.147
d40	0.980**	(2.88)	0.967*	(2.12)	-0.783**	(-2.87)	0.744*	(2.52)	0.003	(0.02)	299	0.112
d41	0.983***	(7.67)	1.005***	(5.50)	-0.489**	(-2.60)	0.171	(1.45)	0.025	(0.35)	747	0.213
d42	0.682***	(10.39)	1.097***	(10.60)	0.158	(1.61)	0.174*	(2.44)	0.075	(1.62)	1751	0.206
d43	1.124***	(4.53)	0.507	(1.74)	-0.125	(-0.54)	0.205	(0.99)	-0.173	(-1.40)	406	0.083
d44	0.718***	(12.67)	1.064***	(11.75)	0.469***	(4.75)	0.046	(0.62)	0.008	(0.19)	1865	0.251
d45	0.964***	(15.46)	1.098***	(8.03)	0.425**	(3.08)	-0.020	(-0.30)	0.041	(1.03)	3776	0.263
d46	1.138***	(28.15)	1.010***	(11.64)	0.200*	(2.40)	0.026	(0.47)	-0.048	(-1.18)	3776	0.277
d47	1.167***	(19.81)	1.172***	(11.17)	0.192	(1.47)	-0.197*	(-2.40)	-0.025	(-0.47)	3442	0.240
d48	0.660***	(7.80)	0.891***	(5.40)	0.316	(1.85)	0.021	(0.19)	0.034	(0.53)	3776	0.064

t statistics in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Notes: Regression coefficients for each dual-class firm's excess returns on the stock market for the entire time period between 2003 and 2017. N is the number of observations (trading days) per firm where 3,776 is the maximum value for firms that listed before 2003. List of ticker and Permno for each individual security can be found in Table A5.

Table A3: Individual regression coefficients for single-class firms

	RMRF		**SMB**		**HML**		**UMD**		**CONS**		**N**	**adj. R^2**
s1	1.058***	(37.72)	-0.334***	(-7.46)	-0.490***	(-9.34)	-0.049	(-1.64)	0.012	(0.63)	3776	0.495
s2	1.084***	(20.45)	0.128	(1.54)	-0.445***	(-5.21)	0.095	(1.95)	0.073*	(2.30)	3776	0.273
s3	1.125***	(28.84)	0.154*	(2.17)	-0.322***	(-4.26)	-0.091*	(-2.13)	0.016	(0.57)	3776	0.362
s4	1.130***	(40.24)	-0.043	(-0.86)	-0.438***	(-8.46)	-0.119***	(-3.45)	0.006	(0.28)	3776	0.491
s5	1.111***	(45.54)	-0.043	(-0.90)	-0.458***	(-7.97)	-0.043	(-1.39)	0.009	(0.42)	3776	0.472
s6	1.384***	(28.93)	0.341***	(4.15)	-0.629***	(-6.65)	-0.045	(-0.77)	0.081*	(2.13)	3385	0.343
s7	1.293***	(33.30)	0.267***	(3.84)	-0.248***	(-3.33)	0.051	(1.26)	0.051	(1.75)	3776	0.403
s8	1.404***	(12.14)	0.123	(0.79)	0.041	(0.33)	-0.189	(-1.71)	0.024	(0.35)	524	0.313
s9	1.181***	(38.52)	0.315***	(5.50)	-0.265***	(-3.89)	-0.061	(-1.57)	0.042	(1.95)	3776	0.528
s10	1.431***	(25.72)	0.949***	(10.19)	-0.590***	(-4.93)	-0.005	(-0.07)	0.045	(1.04)	3776	0.304
s11	1.019***	(35.84)	0.030	(0.54)	-0.216***	(-3.71)	-0.009	(-0.28)	0.000	(0)	3776	0.416
s12	1.689***	(18.45)	0.885***	(6.02)	-1.176***	(-6.95)	-0.272**	(-2.76)	0.014	(0.22)	1414	0.314
s13	0.978***	(31.89)	0.006	(0.12)	-0.148**	(-2.77)	0.000	(-0.01)	0.025	(1.13)	3776	0.397
s14	1.060***	(29.20)	0.587***	(8.59)	-0.217***	(-3.57)	0.011	(0.30)	0.057*	(2.22)	3776	0.407
s15	0.830***	(29.72)	0.316***	(7.29)	-0.250***	(-4.75)	0.014	(0.48)	0.009	(0.37)	3776	0.322
s16	1.110***	(22.81)	0.541***	(5.85)	-0.200*	(-2.44)	0.048	(0.87)	0.037	(0.90)	3776	0.216
s17	1.199***	(32.12)	0.175*	(2.46)	-0.441***	(-5.96)	-0.106*	(-2.34)	0.046	(1.56)	3776	0.363
s18	1.186***	(28.38)	0.537***	(6.97)	-0.293***	(-3.46)	-0.149**	(-2.77)	0.022	(0.60)	3776	0.288
s19	1.514***	(26.73)	1.174***	(11.62)	-0.258*	(-2.28)	-0.250**	(-3.10)	0.006	(0.14)	3776	0.328
s20	1.262***	(31.15)	0.437***	(6.52)	-0.446***	(-5.76)	-0.163**	(-3.13)	0.014	(0.41)	3776	0.333
s21	0.929***	(27.96)	0.756***	(12.77)	-0.220***	(-3.58)	0.143***	(3.93)	0.071**	(2.59)	3776	0.328
s22	1.131***	(5.21)	0.313	(1.09)	-1.157**	(-3.12)	-0.373	(-1.54)	0.132	(0.88)	748	0.066

s23	0.959***	(30.26)	0.580***	(9.85)	-0.257***	(-4.45)	0.024	(0.67)	0.002	(0.08)	3776	0.422
s24	1.087***	(19.92)	0.679***	(5.93)	0.228*	(2.18)	-0.106	(-1.93)	0.046	(1.46)	3220	0.423
s25	0.716***	(14.77)	0.300***	(3.87)	-0.095	(-1.05)	-0.029	(-0.52)	0.019	(0.55)	2602	0.223
s26	1.071***	(23.55)	0.927***	(12.65)	0.257**	(3.19)	0.005	(0.10)	0.036	(1.22)	3776	0.406
s27	1.214***	(29.02)	0.727***	(8.61)	-0.130	(-1.47)	-0.068	(-1.50)	0.009	(0.23)	3776	0.296
s28	1.032***	(21.96)	0.941***	(11.50)	-0.237**	(-2.58)	0.003	(0.05)	0.065	(1.54)	3776	0.220
s29	1.124***	(9.25)	0.701***	(4.16)	-0.973***	(-4.48)	-0.075	(-0.68)	0.049	(0.66)	747	0.237
s30	1.412***	(31.85)	1.137***	(10.84)	0.310***	(3.67)	-0.212***	(-3.81)	0.007	(0.24)	3776	0.549
s31	1.039***	(34.47)	0.897***	(16.11)	-0.182**	(-3.06)	-0.190***	(-4.53)	-0.003	(-0.10)	3776	0.419
s32	1.312***	(4.14)	0.612*	(2.01)	-0.847*	(-2.30)	0.179	(0.68)	-0.036	(-0.24)	290	0.110
s33	1.100***	(18.31)	0.738***	(6.73)	-0.244*	(-2.32)	0.055	(0.89)	0.024	(0.55)	2817	0.286
s34	1.277***	(33.65)	1.187***	(15.03)	0.030	(0.36)	-0.039	(-0.69)	0.022	(0.62)	3776	0.387
s35	0.965***	(8.56)	1.072***	(6.62)	-0.822***	(-4.41)	0.114	(1.05)	0.093	(1.21)	933	0.184
s36	1.169***	(26.22)	0.976***	(11.21)	-0.216**	(-2.76)	-0.019	(-0.38)	0.018	(0.45)	3610	0.294
s37	0.829***	(22.53)	0.714***	(10.27)	-0.026	(-0.30)	0.039	(0.81)	0.014	(0.44)	3776	0.236
s38	0.956***	(14.53)	1.167***	(10.09)	0.021	(0.17)	0.0514	(0.83)	0.041	(0.84)	2601	0.262
s39	1.167***	(21.19)	1.440***	(14.18)	0.316**	(2.87)	-0.214**	(-3.11)	0.022	(0.55)	3776	0.348
s40	1.479***	(8.05)	1.004**	(3.00)	-0.674*	(-2.29)	0.112	(0.72)	-0.048	(-0.41)	599	0.194
s41	1.198***	(14.30)	1.017***	(7.39)	0.085	(0.60)	0.010	(0.12)	0.036	(0.64)	3039	0.233
s42	0.747***	(8.59)	0.702***	(4.46)	-0.046	(-0.25)	0.136	(1.08)	0.074	(1.18)	3776	0.060
s43	0.867***	(10.20)	1.002***	(7.08)	-0.179	(-1.17)	0.219	(1.89)	0.026	(0.39)	1587	0.121
s44	1.045***	(23.45)	1.240***	(14.76)	0.099	(1.07)	-0.148**	(-2.60)	0.004	(0.10)	3776	0.280
s45	0.818***	(8.72)	1.306***	(8.29)	-0.149	(-1.12)	-0.112	(-1.44)	0.026	(0.54)	3776	0.159
s46	0.680***	(9.53)	0.748***	(5.30)	0.179	(1.41)	0.050	(0.61)	0.023	(0.46)	3776	0.094
s47	0.290**	(2.77)	0.619***	(3.42)	-0.242	(-1.34)	0.056	(0.48)	0.127	(1.73)	3776	0.013
s48	0.876***	(9.20)	0.155	(0.92)	-0.505*	(-2.35)	-0.037	(-0.26)	0.071	(0.88)	3776	0.038

t statistics in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Notes: Regression coefficients for each single-class firm's excess returns on the stock market for the entire time period between 2003 and 2017. N is the number of observations (trading days) per firm where 3,776 is the maximum value for firms that listed before 2003. List of ticker and Permno for each individual security can be found in Table A5.

Table A4: Wilcoxon Signed Rank Test

	T	N	Z	Prob.>
RMRF	428.5	44	-0.77	0.2206
SMB	531.0	48	-0.58	0.2811
HML	394.0	48	-1.98	0.0236
UMD	390.0	47	-1.84	0.0332
CONS	448.0	44	-0.54	0.2937

Notes: Wilcoxon Signed Rank Test for test of the null hypothesis that the means of coefficient differences between dual-class firms and their matched single-class equivalents are centred round 0. Coefficient differences smaller than 0.001 are discarded in the test as they can be viewed as being 0. T is the smallest sum of the positive and negative ranks (Wilcoxon signed rank statistic). As N > 20 for all tests, normal approximation can be used and is calculated with correction for continuity. Prob. displays the significance level for each test.

Table A5: Matching of firms

	Dual-class		Single-class	
Number	**Ticker**	**PERMNO**	**Ticker**	**PERMNO**
1	GOOGL	90319	MSFT	10107
2	FB	13407	ATVI	79678
3	BABA	14888	EBAY	86356
4	V	92611	INTC	59328
5	MA	91233	ORCL	10104
6	BIDU	90857	CRM	90215
7	VMW	92257	CTSH	86158
8	WDAY	13628	HPE	15707
9	WB	14616	APH	84769
10	SQ	15826	SWKS	45911
11	DVMT	16267	CA	25778
12	SHOP	15358	SPLK	13379
13	FDC	15703	TSS	76639
14	TEAM	15909	ANSS	83621
15	YNDX	12799	SNPS	77357
16	IAC	78840	TTWO	84761
17	MTCH	15850	VRSN	85753
18	WUBA	14209	MRVL	88360
19	ZG	12927	QRVO	85035
20	SINA	88196	JNPR	86979
21	NTNX	16304	TYL	76185
22	YY	13701	MOMO	15135
23	DATA	13914	NATI	81501
24	DLB	90550	WEX	90569
25	BAH	12366	G	92261
26	SATS	92469	LFUS	77918
27	RNG	14136	NUAN	82759
28	PSTG	15729	PEGA	83779
29	TWLO	16140	NEWR	15108

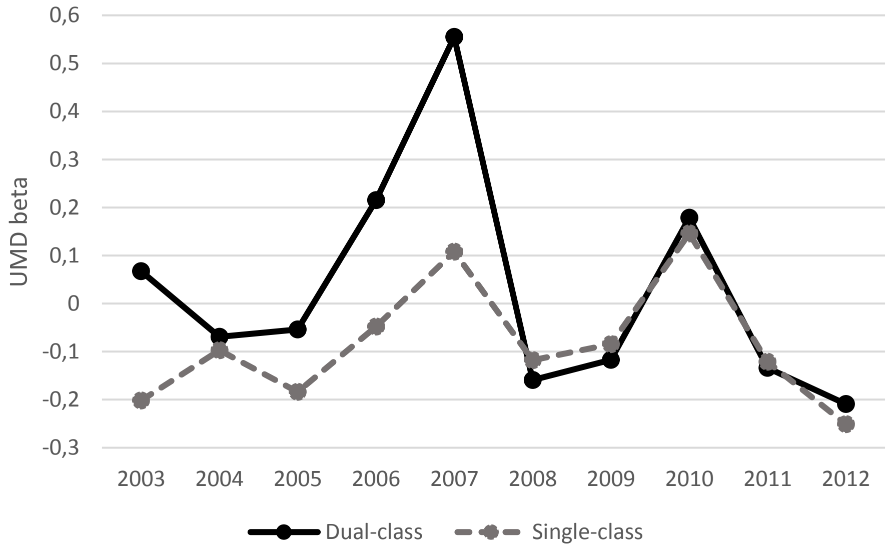
30	ZNGA	13169	BDC	79668
31	VSH	57808	CCMP	88152
32	BOX	15145	COUP	16382
33	TTD	16309	CVLT	91463
34	MANT	89307	PLXS	10032
35	SFUN	12293	QTWO	14516
36	MB	15430	NTGR	89800
37	MSTR	86211	CSGS	83124
38	LXFT	14010	VRTU	92229
39	FIT	15390	NSIT	81220
40	APTI	16282	RPD	15541
41	WK	15119	WEB	90984
42	QADA	12493	CAMP	20670
43	SCWX	16020	CARB	12960
44	VPG	93426	DAKT	80233
45	AMSWA	13777	PDFS	89044
46	RNWK	85576	CTG	26084
47	MCHX	90088	DWCH	77630
48	WSTL	82762	NTWK	87508

Notes: Description of ticker and Permno of each dual-class firm and their matched single-class equivalent used in the study. The numbers in the first left column further correspond to the numbers in Table A2 and Table A3. Permno is the permanent security identification number assigned by the Center for Research in Security Prices (CRSP) to each security.

Figure A1: HML beta over time

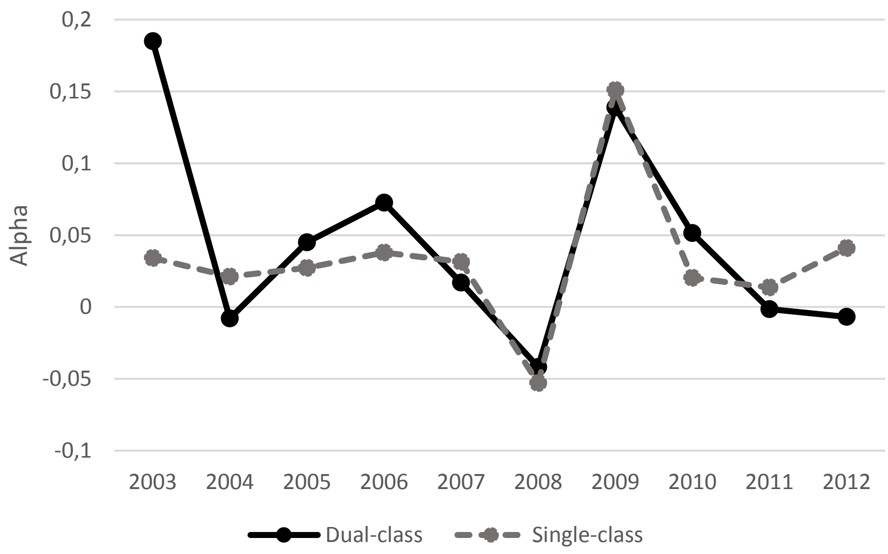
Notes: Development of exposure to HML over time for the dual- and single-class portfolio. Values are based on the third row of regression coefficients in Table 8 and Table 9.

Figure A2: UMD beta over time



Notes: Development of momentum beta over time for the dual- and single-class portfolio. Values are based on the fourth row of regression coefficients in Table 8 and Table 9.

Figure A3: Abnormal returns over time



Notes: Development of abnormal returns over time for the dual- and single-class portfolio. Values are based on the fifth row of regression coefficients in Table 8 and Table 9.