DUAL-CLASS SHARES AND INNOVATION

EVIDENCE FROM THE SWEDISH MARKET

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Dual-class Shares and Innovation: Evidence from the Swedish Market

Abstract:

Dual-class share structures have long been a controversial topic due to their separation between voting and cash flow rights. This thesis examines the relationship between dual-class share structures and innovation in Sweden. The analysis is based on a sample of 2,441 firm-year observations of firms listed on Nasdaq Stockholm and First North Growth Market during the period 2009-2019. We measure innovation using the number of patents, R&D efficiency, and R&D intensity. Contrary to our hypotheses we find that dual-class shares have no significant association with any of the examined innovation measures. We further investigate subsamples of high-tech vs low-tech firms, young vs old firms, and firms that operate in industries with high- vs low industry concentration. We notice a possibly positive association between dual-class shares and the number of patents in high-concentration industries. The findings of this paper are relevant to further shed light on the implications of unequal voting rights in Sweden.

Keywords:

Dual-class shares, Innovation, Patents, Research & Development

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1. Introduction

In a typical public corporation, all shareholders have equal voting and cash flow rights. Dual-class share structures go against this concept of “one share one vote” and allow some shareholders to hold a disproportionate amount of voting rights compared to cash flow exposure. Commonly, the second class of shares with superior voting rights are privately held and controlled by firm founders and management. Because of this separation of voting rights and economic interests, the dual-class share structure has received a lot of criticism over the years (Howell, 2017).

The controversy surrounding the adoption of dual-class share structures began almost a century ago with the Dodge Brothers’ IPO in 1925 (Seligman, 1986). Dodge Brothers’ investment bank owners listed the company, raising $130 million in bonds, non-voting, and preference shares while paying a mere $2.3m for 100 percent of voting rights in the company. Three years later the dual-class share structure was banned from the New York Stock Exchange (NYSE). It wasn’t until the 1980s that NYSE revised its position on the matter after being faced with competition from Nasdaq (Hughes, 2015). It is not only in the US that the dual-class share structure has faced opposition, but several jurisdictions have for long had an outright ban in place. Singapore and Hong Kong did not allow dual-class listings until as recently as 2018. The decision to allow dual-class shares was in both cases prompted by high-profile companies considering other stock exchanges because of the ban. In the case of Hong Kong, it was the story of how Alibaba chose NYSE for its 25 billion USD IPO in 2014 after the Hong Kong Stock Exchange did not accept its proposed dual-class share structure (Lidman & Skog, 2022).

In Sweden, dual-class listings have been an important feature of the stock market for approximately 100 years (Lidman & Skog, 2022). The power dynamics in the Swedish market are characterized by concentrated control through unequal voting rights, with prominent examples being the Wallenberg Group’s Investor and Fredrik Lundberg’s Industrivärden. Both these actors control a disproportionately large share of Swedish companies compared to the amount of equity invested. One example is the Swedish telecom giant, Ericsson, where they together control almost 39% of votes while holding less than 11% of equity (Jönsson, 2023). Following the rising ESG awareness, the occurrence of unequal voting rights has now come to the attention of ISS, the powerful US advising firm.[1] ISS argues that unequal voting rights constitute bad corporate governance and in its updated policy document promises to hold boards accountable for this. Starting from 2024 ISS will generally recommend voting against directors maintaining a corporate structure with unequal voting rights. The policy change has been met with strong opposition in Sweden, particularly from The Confederation of Swedish

[1] Institutional Shareholder Services (ISS) is a leading provider of corporate governance and responsible investment solutions as well as proxy voting services at annual shareholder meetings.

Enterprise, which argues that the policy change demonstrates a lack of understanding of the continental European praxis with unequal voting rights (Rex, 2022).

In recent years there has been an increasing popularity to adopt the dual-class share structure around the world, especially in high-tech companies. Several high-profile IPOs such as Facebook, Google, Lyft, and Snap have adopted the dual-class share structure. The increasing number of dual-class listings, and the corresponding desire by stock exchanges to attract public offerings, has caused a renewed interest in the structure (Committee on capital markets regulation, 2020). Even though the dual-class structure is gaining popularity, especially among innovative entrepreneurial firms, there is little evidence of how it affects innovation. Some studies suggest that the dual-class share structure positively influences firms' innovation (Cao et al., 2020; Baran et al., 2022), whilst others argue that the share structure leads to exacerbated agency costs (Masulis et al., 2009; Gompers et al., 2010). Taking both these views into account, the overall effect of dual-class share structures on innovation is ambiguous. This is relevant to investigate for several reasons; corporations should choose to adopt a governance system that provides them with the highest likelihood of success, and regulators should promote a system that protects shareholders' interests.

Sweden is one of the countries where the separation between votes and capital is most common, and the case is often mentioned in the literature (Bebchuk et al., 2000; La Porta et al., 1999). However, most previous research surrounding dual-class share structures and innovation has been conducted in the US market, where the share structure rather is the exception than the rule. Since corporate laws and shareholder protection differ across the world it is reasonable to assume that results may vary in different countries. To our knowledge, there is no prior research investigating the dual-class share structure and its association with innovation in a Swedish setting. This paper aims to contribute by filling this gap and providing a Swedish perspective on the topic.

This paper is structured as follows: Section 2 presents a literature review and proceeds to formulate the relevant hypothesis. Section 3 describes the data collection process and methodology used to examine our hypotheses. Section 4 presents the results of our tests. Section 5 presents results from relevant robustness tests. Section 6 presents an analysis of the results connecting to existing literature. Lastly, section 7 concludes our results and provides suggestions for future research.

2. Literature review and hypothesis formulation

Innovation has long been regarded as a vital component to achieve economic growth and building competitive advantage (Solow, 1957). While there seems to be a consensus regarding the importance of innovation, investments in innovation have in the past been sacrificed at times, for instance, to smooth earnings and meet short-term earnings estimates (Graham et al., 2005). The changing business environment, with an ever-transforming competitive climate, is forcing companies to move innovation up on the agenda. Market research has shown a trend of increasing appetite for innovation as more companies recognize its importance in sustaining growth. An increasing number of CEOs have stated that they are now taking personal responsibility for directing and inspiring innovation as it has become an ever more vital element of success and business survival (PwC, 2013). Successful companies recognize that innovation is no longer at the sidelines of the business but rather a mainstream process, former CEO of Apple even stated that "*innovation is the only way to win*" (Jobs, 1999).

The optimal innovation-motivating incentive scheme has been shown to exhibit tolerance for early failure, reward for long-term success, and job security (Manso, 2011). There are several different ways in which a company can achieve these characteristics. An important body of research has connected the concept of innovation to differential ownership. In private firms, insiders are more tolerant of failures and thus more inclined to invest in innovation (Ferreira et al., 2014). Holmström (1989) famously argues that public capital markets force managers to focus on short-term projects and neglect innovation. Bernstein et al. (2015) examined the effects of going public on innovation and found that going public changes the strategy in which firms pursue innovation. The study shows that the quality of internal innovation declines following the initial public offering, and that there is a lower quality of innovation as well as more exploitative patents among public firms compared to private firms. The innovation decline is explained by increased agency problems that come with being public and increased managerial career concerns. Adding on to this, Ferreira et al. (2014) suggest that public firms are less likely to engage in product market innovation. DeAngelo and DeAngelo (1985) argue that the dual-class share structure provides companies with the opportunity of having a hybrid between public and private ownership. This view is motivated by the fact that dual-class firms maintain the benefits offered to private firms, such as autonomy and increased tolerance for innovative failure, while at the same time having access to the public capital market. Then the question remains, how does this form of ownership structure affect innovation?

Baran et al. (2022) argue that the dual-class share structure affects innovation through two main mechanisms: *takeover protection* and *disproportionate insider control*. The *takeover protection* mechanism is not unique to the dual-class share structure, this sort of "external entrenchment" can also be facilitated through other anti-takeover measures (i.e., poison pills, staggered boards, etc.). Nevertheless, firms with dual-class share structures are virtually immune to hostile takeovers (Gompers et al. 2010). On the other hand, the "internal entrenchment" facilitated through *disproportionate insider control* is distinct for the dual-class share structure. This internal entrenchment protects management from internal opposition by diminishing shareholder democracy. When analyzing the effects of these mechanisms, they both have aspects through which they can either encourage or stifle innovation. By protecting firms from hostile takeovers, managers are provided with job security and are thus allowed to have a long-term focus. Job security, however, also allows managers to slack and exercise private benefits of control; meaning to achieve economic gain at the expense of minority shareholders. *Disproportionate insider control* may diminish shareholder democracy and lead to incompetent management exercising private benefits of control. On the other hand, it may also provide the company with long-term stable management, more autonomy, flexibility, and a higher tolerance for failure, creating an environment that encourages innovation. The dual-class share structure can thus be thought of as a double-edged sword for companies. Since the mechanisms can go both ways, several studies have tried to establish what the overall effect of the share structure is.

One stream of research argues that the negative effects carry the most weight, this view is regarded as the agency cost view. Authors supporting this view argue that the dual-class share structure may exacerbate the conflict between principals and agents, which presents itself when controlling shareholders seek private benefits at the expense of minority shareholders (Jensen & Meckling, 1976; Masulis et al., 2009; Gompers et al., 2010). Agency costs be displayed in different forms, for example as inefficiencies in the market for corporate control (Grossman & Hart, 1988), distortions in investment decisions (Bebchuk et al., 2000), tunneling (Johnson et al., 2000), and inefficient perk consumption (Yermack, 2006). Masulis et al. (2009) examine US firms during the time 1994-2002 and find that dual-class companies' cash holdings are valued less by shareholders, acquisitions generate lower returns, CEOs receive higher excess compensation, and capital expenditures contribute less to shareholder wealth compared to the single-class companies. Further support for the agency cost view is provided by Gompers et al. (2010) who examine the incentive and entrenchment effects in dual-class firms on firm value in the US during the same period. The results show that firm value is positively associated with insiders' cash-flow rights, negatively associated with insiders' voting rights, and negatively associated with the wedge between voting- and cash-flow rights. All these results point to dual-class firms having exacerbated agency problems and greater private benefits to managers at the expense of minority shareholders. Furthermore, Atanassov (2013) finds a significant decline in the number of patents and patent citations for firms that are incorporated in states that pass antitakeover laws, suggesting that hostile takeovers are beneficial in the case of innovation. Although this research is not linked to the dual-class share structure per se, it does shed light on the effects of the *takeover protection mechanism* that the share structure may contribute to.

The opposing stream of research is focused on the innovation view (Baran et al., 2022; Cao et al., 2020; Chemmanur & Jiao, 2012; Cheng et al., 2020; Jordan et al., 2016). This view suggests that the dual-class share structure may insulate managers from short-term profitability pressure from the market and thus encourage innovation by facilitating long-term strategies. Although there is evidence supporting this view, it is not always black and white and has sometimes been shown to be conditional on certain factors. Chemmanur and Jiao (2012) recognize that one type of manager in dual-class firms may use the increased control to enjoy private benefits, but they also suggest an alternate scenario where another type of manager instead uses the security benefits to create considerable value. The study shows that under the single-class share structure, managers have a greater chance of losing control to rivals when undertaking projects with high near-term uncertainty. By adopting the dual-class share structure, managers have enough votes to prevail against rivals, but this power may also be misused by managers simply wanting to enjoy the private benefits of control. Jordan et al. (2016) agree with the idea that dual-class firms face lower short-term market pressure, and further argue that this enables them to focus on the implementation of long-term projects. They also find that dual-class firms exhibit more growth opportunities in terms of higher sales growth and R&D intensity. Whilst Jordan et al. (2016) established that dual-class firms are more R&D intense, Cheng et al. (2020) examine how the share structure affects investment efficiency. When comparing the investment efficiency between dual- and single-class firms, they find that dual-class firms invest more efficiently. The authors respond to the previous criticism about the increased agency costs of dual-class share structure and, in line with Chemmanur and Jiao (2012), suggest that insiders instead might use the increased control for noble purposes.

Further support of the innovation view is presented by Cao et al. (2020) and Baran et al. (2022) who go into more detail about how dual-class shares are associated with different measures of innovation, more specifically the number of patents, quality of patents, and efficiency of R&D usage. Cao et al. (2020) examine the relationship between dual-class share structure and innovation in the US over the period 1976-2006. They find that dual-class shares have no association with patent counts but a positive causality relationship with innovation quality, measured by patent citations. However, the positive effect of dual-class share structures is only prevalent when there are market disciplining forces, for example in high-tech sectors where firms generally face great competition and need to invest in R&D for long-term projects. However, it remains unclear whether these associations are specific to the dual-class share structure or whether they might stem from the positive effect that any *takeover protection* could have on innovation. Baran et al. (2022) aim to fill this gap by specifically examining the impact of *disproportionate insider control* on innovation. This is achieved by examining a sample of US dual-classed firms matched with single-class firms possessing similar anti-takeover protection during the period 2000-2008. The study finds a positive association between dual-class share structure and both the number and quality of patents as well as the efficiency of R&D

usage, suggesting that it is not just the *takeover protection* mechanism that influences the innovative output. Moreover, the positive effects were found to be conditional on the presence of *specific insiders* and dissipate within 10 years post-IPO. They further divided the sample into different subsamples and found that positive effects were concentrated in financially constrained firms and firms in highly competitive industries. This supports the view presented by Li et al. (2019) that the ability of insiders to act quickly and decisively to capture innovative opportunities is more beneficial when there is high industry competition.

Interesting to note is that even before introducing the control for *specific insiders,* the positive association between dual-class shares and the number of patents in the Baran et al. (2022) study was already significant. This goes against the results presented by Cao et al. (2020) who found no association between dual-class shares and the number of patents. The differences between the studies are mainly that Baran et al. (2022) specifically examined the impact of *disproportionate insider control* and not the *takeover protection* mechanism, but also that they cover a shorter period. Consequently, a potential explanation for the differing results might be that the *takeover protection* mechanism may not be beneficial in the case of innovation (Atanassov, 2013), whilst *disproportionate insider control* is (Baran et al., 2022), but it might also be due to differing periods.

Most previous research surrounding dual-class share structures has been conducted in the US market. Adams and Ferreira (2008) argue that the effects of dual-class share structures may differ across the world depending on corporate law and national shareholder protection. This paper aims to contribute by providing a Swedish perspective on the topic. Since Sweden is one of the countries where the separation between votes and capital is most common, it is an interesting market to study. As previously mentioned, when studying the US market, it is argued that dual-class firms are virtually immune to hostile takeovers, making the *takeover protection* mechanism one of the main mechanisms by which dual-class share structures may impact innovation. However, when studying the Swedish takeover market, Skog (2004) presents a different view. By examining empirical data from the Swedish takeover market, he tried to disentangle whether takeovers are less common among dual-class firms, which would suggest that there is a *takeover protection* embedded in the share structure. He looked at Swedish listed companies that were subject to takeovers during 1990-2002 and concluded that 64% of these were dual-class firms, which is not significantly lower than the average frequency of dual-class firms over the same period (69%). The author thus argues that the dual-class share structure does not prevent takeovers in Sweden, suggesting that the *takeover protection* mechanism by which dual-class share structures affect innovation may not be as important in Sweden as in the US.

The other mechanism by which dual-class share structures are expected to affect innovation is through internal entrenchment facilitated by *disproportionate insider control.* The presence of *disproportionate insider control* may lead to minority shareholder expropriation, or it may, under the right circumstances, promote an environment that fosters innovation. Building on results from Baran et al. (2022) it is expected that this mechanism has a positive association with dual-class shares, mainly when there are *specific insiders* present. However, there are other ways to defer potential expropriation brought on by *disproportionate insider control*, for example through better legal protection and stronger social norms (Holmén & Knopf, 2004). Sweden's legal system is ranked by Johnson et al. (2000) to be at the world average regarding minority shareholder protection, therefore it is not expected to offset the weak corporate governance. Even though Sweden's legal system ranks comparatively low in shareholder protection, Coffee (2001) demonstrates that Sweden seems to outperform the US in terms of reducing private benefits of control. The explanation for this may lay in extralegal institutions (i.e., organized labor, press, tax compliance, and norms) that affect shareholder protection (Coffee, 2001; Dyck & Zingales, 2004). Sweden has strong extra-legal institutions in the form of social norms, tax compliance, and press that provide the country with higher minority shareholder protection and appears to discourage clear wealth transfers from the minority to controlling shareholders (Holmén & Knopf, 2004).

Following the study by Cao et al. (2020), we do not isolate the association of a specific mechanism with dual-class shares, or control for specific insiders, but rather want to test the overall net effect of the mechanisms in Sweden. However, due to the characteristics of the Swedish market presented above, we hypothesize that the dual-class share structure is positively associated with the number of patents, R&D efficiency, and R&D intensity among Swedish public firms. The formulated hypotheses are as follows:

H1: Dual-class share structure is positively associated with innovation activity, measured by the number of patents, among Swedish public firms.

H2: Dual-class share structure is positively associated with R&D efficiency, measured by the number of patents per R&D expenditure, among Swedish public firms.

H3: Dual-class share structure is positively associated with R&D intensity, measured by R&D expenditure scaled by company assets, among Swedish public firms.

3. Data and methodology

In this section, we describe the process of collecting patent-, financial-, and stock data. We also present the chosen variables, descriptive statistics, and methodology used to analyze the data.

3.1. Data Collection

3.1.1. Patent data

The patent data is retrieved from the PAtLink database, which records all patent filings, which were ultimately granted, of Swedish firms for the period 1991-2021 and the companies' corresponding organization numbers. PAtLink extracts patent data from Patstat, which is based on EPO's (European Patent Office) databases, and organization numbers from Serrano. The dataset holds information on application authority, application filing year, application ID, application kind, applicant/inventor name, and simple patent family ID.

Using PAtLink, we construct firm-year observations of the total number of innovations patented for each firm for a given year, for the period 2009-2019. This is done by computing the patent count for each year and each organization's number. Since a single innovation can be patented in several countries and regions, we avoid the issue of double-counting innovations by basing the patent count on unique patent identifiers.

One issue we encounter at this stage is that the first, out of four, of PAtLink's datasets is lacking data on unique patent identifiers. We resolve this issue by matching the data in the first dataset to the three other datasets and by removing all observations with exact matches from the first dataset. This leaves us with 4,175 unique observations without a unique patent identifier. We decide to include these in our patent data, resulting in our patent data containing 204,718 observations. Whilst we deem the choice to include the unique observations from the first dataset to have minimal effect on our results, given its small magnitude, it is worth noting that this may lead to a slight upwards bias in our patent count, due to the risk of double counting these patents.

3.1.2. Stock data

Annual stock data is collected from FinBas. The Finbas database contains daily end-of-day stock price data, corporate actions, and fundamentals from the Nordic stock exchanges, including Nasdaq Stockholm and Nasdaq First North Growth Market, formerly known as the Stockholm Stock Exchange and Stockholm Stock Exchange First North respectively. The data for the Swedish markets date back to 1912.

Market capitalization data, share structure information, and the number of years since the initial public offering during the period 1998-2021 are retrieved for companies on Nasdaq Stockholm and Nasdaq First North Growth Market. Since this thesis examines the effect of dual-class shares with disproportionate voting rights in Sweden, observations of non-voting shares are excluded, these include preference shares, D-shares, and R-shares. Furthermore, observations with companies headquartered in a foreign country are excluded. Lastly, SPACs (special purpose acquisition company) shares are dropped as well.

Following Cao et al. (2020) we construct firm-year data of share class structure for the years 2009-2019 by classifying a company as having a dual-class share structure if their share class contains a letter (A, B, or C) and as a single-class share structure otherwise. Lastly, for the companies in our sample covering the years 2009-2019, we retrieve the first year of listing on either the Nasdaq Stockholm or Nasdaq First North Growth Market to construct age data. If one of the companies in our sample is listed in the year 1998, they are categorized as “over 10 years” for all observations in our sample.

This process results in our stock dataset containing 450 firms and 3,852 firm-year observations. See Table 3 for the final number of dual- and single-class share structure observations per year, after dropping additional observations as described below.

3.1.3. Financial data

Financial data is collected from WRDS’s Compustat database, a database with financial, statistical, and market information on active and inactive global companies. The database is published by Standard and Poor’s and contains data dating back to 1950. Orbis, a database containing financial information for public and private companies, is used to complement R&D expenditure data due to missing data in the Compustat database.

We further collect annual consolidated accounting data for the period 2008-2019, for companies with Swedish ISIN identifiers, to construct a dataset of our control variables. The collected data includes ISIN number, R&D expenditure, total assets, revenue, earnings before interest and taxes, total debt, book value of equity, and capital expenditure.

For observations with missing R&D expenditure data in Compustat, we collect R&D expenditure from Orbis. By matching these observations through ISIN identifiers, this data is integrated into our financial dataset from Compustat. Following the method employed by Cao et al. (2020), R&D expenditure data which is still missing is replaced by 0, this is done for 188 observations included in the final dataset.

Also following Cao et al. (2020), we exclude observations that belong to the financials sector. Similarly, due to incomparable financial data, we exclude the real estate sector from our sample. Further, the energy and utilities sector are also excluded, due to high state regulation making these companies fundamentally different from the rest of the economy. The sectors are based on 2-digit GICS industry codes. Lastly, observations with 0 or negative revenue or total assets are excluded. Only observations on companies in our stock data sample are included. Then, our dataset of various controls (covered in section 3.2.2) is constructed for the period 2009-2019. This gives us a sample consisting of 2,441 firm-year observations.

3.1.4. Data consolidation

Firstly, the firm-year observations of the patent count are aggregated to group level for each public company and year in our study, thereby excluding any patent filed by any other company than those in our sample and their subsidiaries. This is achieved with the help of the Serrano database, which includes data on firms´ ultimate parent company. However, this entails two issues. Firstly, some of the organization numbers in PAtLink do not match with any organization number in Serrano. Secondly, public Swedish companies, and their subsidiaries, that are ultimately owned by another company do not have the correct parent organization number recorded in Serrano for aggregating at the public firms' group level. These issues are both resolved by manually adjusting organization numbers in PAtLink and Serrano, such that the patent data match with Serrano and the patent count is correctly aggregated at the group level, using the organization numbers found in the database Retriever and from company annual reports. Our final sample of patents consists of 33,639 patent applications in total[2].

Secondly, the aggregated patent data is merged with the stock data by matching organization numbers. For this step, the public companies' organization numbers are manually inserted in the FinBas database, after retrieving the organization numbers from the Retriever and Serrano databases.

Lastly, the aggregated patent and stock data are merged with the accounting data in Compustat by matching ISIN identifiers. This also requires manually adjusting the ISIN identifiers since some companies do not have matching identifiers between the FinBas and Compustat databases. Finally, all firm-year observations where the company is not public on either the Nasdaq Stockholm or Nasdaq First North Growth Market are dropped, resulting in our final dataset consisting of 2,441 firm-year observations.

3.2. Variable description

3.2.1. Main variables

The main variables in this study are the number of patents (*Patentcount*) and a dummy variable indicating whether a company has a dual- or single-class share structure (*DCS*). The number of patents granted measures companies' innovative output and has been

[2] The total patent count of all observations after winsorizing at the 1% and 99% level was 17,043

employed as a measure of innovation in many recent studies (e.g., Baran et al., 2022; Cao et al., 2020). Due to fluctuations in the time for patent offices to process applications (Griliches et al., 1986), we have used the patent applications filing year, instead of the year it was granted, as it better matches the time of innovation. There are some caveats to using patent count as a measure of innovation: not all innovations are patented, some are for instance protected as trade secrets. Moreover, it does not measure the quality of the innovation, but considering that patenting is costly and that it requires a certain degree of novelty, the risk of counting innovation with little relevance is most likely reduced. Nonetheless, we choose to analyze patenting activity as it is widely used and regarded as an established measure of innovative outcomes (Amess et al., 2015).

Additionally, we complement the study by analyzing two other measures of innovation: R&D efficiency and R&D intensity. Following Baran et al. (2022), R&D efficiency (*Patentcount/R&D*) is measured by yearly patent count divided by R&D expenditure. R&D intensity (*R&DIntensity*) is measured by R&D expenditure normalized by total assets. When not the main variable of interest, *R&DIntensity* is also used as a control variable. All variables are winsorized at the 1st and 99th percentile to adjust for outliers and extreme values.

3.2.2. Control variables

Based on relevant literature we identify and control for a set of firm characteristics which are deemed to be significant determinants of innovation at the firm level. For our baseline specification, we control for firm size and R&D intensity (*R&DIntensity*). Firm size is measured by the natural logarithm of revenue (*LnSales*). We then construct a more comprehensive specification in which we include the additional controls: profitability (*ROA*), measured by return on assets and computed as earnings before interest and taxes divided by total assets; leverage (*Leverage*), measured by total debt divided by total assets; rate of investment in fixed tangible assets (*CAPEXIntensity*), measured by capital expenditures divided by total assets; and growth opportunities (*TobinsQ*), measured by Tobin's Q and computed by dividing market value of equity by book value of equity. In accordance with our main variables, all control variables are winsorized at the 1st and 99th percentile as well to adjust for outliers and extreme values. Some variables which have been used as controls in previous innovation studies such as firm age, defined as year since IPO, have not been included in our study due to a lack of relevant data in the datasets we used.

3.2.3. Subsamples

Previous literature has found that the effect of dual-class share structures on innovation may differ in different subsamples (Cao et al., 2020, Baran et al., 2022). Consequently, we decide to divide the full sample into subsamples concerning industry, age, and industry concentration. To divide the sample into these different subsamples, some additional variables and definitions are needed. Firstly, the sample is split according to whether the firm is in a high-tech or low-tech industry. The high-tech industry classification is based on 6-digit GICS codes following Kile and Phillips's (2009) recommendations, while low-tech industries are defined as the remainder. Second, the age subsample divides the full sample into young and old firms. The age is computed by taking the year of the observation and subtracting the year of listing on either the Nasdaq Stockholm or Nasdaq First North Growth Market. A firm is categorized as old when it has been listed for more than 10 years. Third, industry concentration is measured by The Herfindahl-Hirschman Index, which is calculated as the sum of the squared market share of each firm within the industry. The Herfindahl-Hirschman index is calculated for each 2-digit GICS industry using yearly revenues for all firms in the Compustat database. Because of limited access to private company information, this measure is not perfect as only revenue data for the public companies were used. Hence, it might not truly reflect the concentration of the whole industry.

3.3. Descriptive statistics

Table 1A

Summary statistics

The table reports summary statistics for the variables constructed from the sample of public Swedish firms from 2009-2020, split by share class structure. The presented statistics are computed after winsorizing the variables at 1% and 99% level. Columns (1) to (4) and (5) to (8) reports the number of observations, mean, median and standard deviation of single-class and dual-class firms. Column (9) reports the t-statistic from testing if the difference in means between the single-class and dual-class sample is 0.

	Single-Class firms				Dual-Class firms				
	Obs	Mean	Median	S.D.	Obs	Mean	Median	S.D.	t-stat
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Dependent variables									
Patentcount	1314	2.64	0.00	11.68	1127	12.04	0.00	40.35	-8.05
Patentcount/R&D	694	0.05	0.00	0.16	582	0.06	0.01	0.22	-1.62
R&DIntensity (%)	1314	4.89	0.09	9.73	1127	3.03	3.03	6.70	-5.41
Control variables									
ROA (%)	1314	2.66	6.50	17.6	1127	6.29	7.75	14.19	-5.55
LnSales	1314	6.90	7.09	2.18	1127	7.86	7.59	2.19	-10.78
TobinsQ	1310	4.31	2.49	6.54	1118	3.64	2.38	4.66	-2.86
Leverage (%)	1314	18.74	16.50	16.16	1127	19.23	17.83	15.26	-0.76
CAPEXIntensity (%)	1236	2.33	1.38	2.73	1100	2.61	1.75	2.61	-2.48

The statistics presented above in Table 1A suggests a right skewness in our dependent variables for both single-class and dual-class firms, with the mean being of significantly larger magnitude than the median for these variables. Further, the t-statistics indicate that the mean values for all the firm characteristics, besides leverage, are statistically significantly different between single-class and dual-class firms. The average dual-class firm in our sample, in comparison to the average single-class firm, files for more patents, whilst having approximately the same level of *Patentcount/R&D* and lower *R&DIntensity*. A significant difference in firm characteristics is that dual-class firms are significantly larger than single-class firms in terms of revenue. The average dual-class company has *LnSales* of 7.86 compared to the average single-class company with 6.90, meaning that the average dual-class firm has approximately 161%[3] higher revenue than the average single-class firm. Other differences we observe are that dual-class firms exhibit higher *ROA*, have higher *leverage*, have lower *TobinsQ,* and have higher *CAPEXIntensity*. These differences in firm characteristics indicate that we should include these control variables in our analyses. Given the significant differences between the groups with regards to *LnSales* and *R&DIntensity,* these controls will be particularly important for our regressions. To further understand our sample, we have separated the full sample into subsamples which are presented in Table 1B below.

Table 1B
Summary statistics

The table presents summary statistics of the innovation measures employed in our study for different subsamples of single-class and dual-class firms. The statistics are computed after winsorizing the variables. The first set of subsamples are companies operating in either low-tech or high-tech industries. The second set of subsamples are young and old firms. The final set of subsamples are companies operating in industries with low or high industry concentration, measured by the Herfindahl-Hirschman index.

	Single-Class firms				**Dual-Class firms**			
	Obs	Mean	Obs	Mean	Obs	Mean	Obs	Mean
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Low vs. High-Tech Firms								
	Low-Tech		High-Tech		Low-Tech		High-Tech	
Patentcount	703	3.40	611	1.77	746	14.00	381	8.19
Patentcount/R&D	287	0.03	407	0.05	328	0.05	254	0.08
R&DIntensity (%)	703	1.40	611	8.90	746	1.16	381	6.69
LnSales	703	7.88	611	6.39	746	8.44	381	6.80
Young vs. Old Firms								
	Young		Old		Young		Old	
Patentcount	729	1.54	585	4.02	233	4.38	894	14.03
Patentcount/R&D	366	0.06	328	0.03	90	0.18	492	0.04
R&DIntensity (%)	729	4.36	585	5.56	233	3.04	894	3.03
LnSales	729	6.65	585	7.22	233	6.78	894	8.14
Low vs. High Industry Concentration								
	Low		High		Low		High	
Patentcount	589	3.72	725	1.77	613	13.72	514	10.03
Patentcount/R&D	365	0.05	329	0.03	345	0.08	237	0.04
R&DIntensity (%)	589	5.87	725	4.10	613	3.10	514	2.93
LnSales	589	6.59	725	7.16	613	8.06	514	7.61

[3] $Sales_{average\ dual}$ / $Sales_{average\ single}$ = $(e^{7.86})/(e^{6.9})$ = 2.611

From Table 1B we can deduce that companies in low-tech industries file more patents on average, with the mean *Patentcount* being significantly larger for low-tech firms, within both the single-class and dual-class groups. Whilst this might be counterintuitive, it is most likely explained by low-tech companies being significantly larger than high-tech companies (average *LnSales* of 8.24 vs. 6.02) and size being an established determinant of innovative activity. Like in the full sample, dual-class companies have higher *Patentcount* and *Patentcount/R&D* on average, whilst having lower average *R&DIntensity* compared to single-class firms. One can also infer that the proportion of high-tech firms within the dual-class group is lower than that of the single-class group. Similarly, the dual-class sample has a lower proportion of young firms in comparison to the single-class group. Lastly, the number of companies in industries with low concentration is about evenly split among the two share structures (589 for single-class vs. 613 in dual-class, in *Patentcount* and *R&DIntensity*), but there are significantly fewer companies within highly concentrated industries that have dual-share class structures. To gain an understanding of our variables' correlations with each other we constructed a correlation matrix presented in Table 2 below.

Table 2

Correlation matrix

The table reports the correlation coefficient between all variables employed in our full model specifications, excluding *Patentcount/R&D*. The statistics were computed after winsorizing the variables, for 2,324 observations in our sample. 117 observations are not accounted for in the correlation matrix due to missing observations in *CAPEXIntensity*.

		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
DCS	(1)	1.00							
Patentcount	(2)	0.16	1.00						
R&DIntensity	(3)	-0.12	0.05	1.00					
ROA	(4)	0.11	0.05	-0.48	1.00				
LnSales	(5)	0.21	0.39	-0.39	0.47	1.00			
Tobins Q	(6)	-0.07	-0.04	0.22	-0.01	-0.20	1.00		
Leverage	(7)	0.03	0.07	-0.24	0.00	0.33	-0.06	1.00	
CAPEXIntensity	(8)	0.04	0.04	-0.15	0.13	0.25	0.06	0.11	1.00

From Table 2 we can infer that *LnSales* and *R&DIntensity* are highly and positively correlated with *Patentcount*. This is to be expected since both R&D expenditure and size are generally known determinants of innovative activity (Hall & Ziedonis, 2001). Moreover, *LnSales* also exhibit a strong positive correlation with *R&DIntensity*. To further understand the characteristics of our sample we constructed Table 3 below that displays the number of patents divided between dual-class and single-class firms over our sample period.

Table 3

No. of Patents, companies with dual- and single-class share structures, and their respective share of total patents, per year

This table presents the total number of patents filed for by 322 public Swedish companies and the number of firms with dual-class and single-class share structure each year, as well their respective share of patent filings by dual and single share class companies, for the period 2009-2019. The annual patent count is computed after the variable have been winsorized the 1% and 99% level.

		Dual-class		Single-class	
	Total patents	Observations	% of patents	Observations	% of patents
	(1)	(2)	(3)	(4)	(5)
2009	1701	107	81%	97	19%
2010	1459	106	84%	96	16%
2011	1653	104	82%	99	18%
2012	1605	99	81%	100	19%
2013	1787	97	80%	99	20%
2014	1749	99	82%	109	18%
2015	1551	98	76%	119	24%
2016	1379	99	76%	137	24%
2017	1514	106	77%	153	23%
2018	1470	107	78%	154	22%
2019	1175	105	77%	151	23%
Total	17043	1127	80%	1314	20%

From Table 3 we can observe that the number of observations with dual-class share structure is slightly higher than single-class share structure in the years 2009-2011. However, the number of single-class share structure observations rapidly increased after 2013. For these later years, there are more observations with single-class share structures than with dual-class share structures, which is opposite from the trend we were expecting to see. Further, one can see that we have an unbalanced sample, with more observations in the later years than at the beginning of our sample period. This highlights the importance of controlling for year-fixed effects in our study. Lastly, as also indicated by the descriptive statistics (Table 1A), companies with dual-class share structures account for a large majority of the total shares of patents for all years. To examine possible differences between sectors in our sample we constructed Table 4 below which presents the share of observations and patents per sector.

Table 4

Share of observations and patents per sector

This table reports the percentage share of total observations and of total patents each sector accounts for. The sector classifications are based on the 2-digit GIC industry codes. The full sample consists of 2,441 observations and 17,043 patent filings, after winsorizing the patent count at 1% and 99% level, for the period 2009-2019.

Sector	Share of observations	Share of patents
Industrials	58%	32%
Information Technology	19%	19%
Consumer Discretionary	9%	15%
Materials	6%	6%
Health Care	5%	19%
Consumer Staples	2%	3%
Communication Services	1%	5%

From Table 4 one can see that industrials constitute the largest group in our sample, both in terms of share of patents (32%) and share of observations (58%). The second largest sector only accounts for 19% of observations and 19% of patents. This highlights the importance of controlling for industry-fixed effects in our study. In terms of *Patentcount*, our dataset contains some companies with large outliers, namely Ericsson, Volvo, and SKF. These account for 14%, 13%, and 12% (38% cumulatively) of the total patents, whilst the 4th largest make up 5%. For completeness in our results, we have decided to include the observations in our sample. However, we run regressions without these observations as a robustness test as well, which is covered in section 5.1 and 5.2.

3.4. Methodology

In this section, we establish the methodology that is used to examine the association between dual-class share structures and our innovation measures. As mentioned in Section 3.2, our study employs a baseline model specification and full model specification with additional controls, the reason for this is to isolate and assess the effect of including additional control variables on our results. The full model specification will be used for our main analysis.

3.4.1. Baseline specification

The baseline specification examines the association between the dual-class share structure and our three innovation measures whilst controlling for size (*LnSales*) and R&D intensity (*R&DIntensity*). In model specification 3a, when *R&DIntensity* is the main variable of interest, we only use *LnSales* as a control. Since previous literature (i.e., Cao et al., 2020; Baran et al., 2022) suggests that innovation varies across sectors, we then also include fixed effects for industry, based on 2-digit GICS industry codes. Moreover, due to our unbalanced dataset, we also include year-fixed effects. We first run a regression with the baseline specification for each dependent variable before adding the industry and year-fixed effects to see how this affects our coefficient estimates. All regressions also use robust standard errors clustered at the firm level. The baseline regression specifications follow:

$$Patentcount_{i,t} = \alpha + \beta_1 DCS_{i,t} + \beta_2 R\&DIntensity_{i,t} + \beta_3 LnSales_{i,t} + \varepsilon_{i,t} \tag{1a}$$

$$Patentcount/R\&D_{i,t} = \alpha + \beta_1 DCS_{i,t} + \beta_2 R\&DIntensity_{i,t} + \beta_3 LnSales_{i,t} + \varepsilon_{i,t} \tag{2a}$$

$$R\&DIntensity_{i,t} = \alpha + \beta_1 DCS_{i,t} + \beta_2 LnSales_{i,t} + \varepsilon_{i,t} \tag{3a}$$

3.4.2. Full specification

The full specification examines the association between the dual-class share structure and our three innovation measures whilst controlling for R&D Intensity (*R&DIntensity*), size (*LnSales*), profitability (*ROA*), leverage (*Leverage*), rate of investment in fixed tangible assets (*CAPEXIntensity*), and growth opportunities (*TobinsQ*). These additional control variables have in previous literature (e.g., Cao et al., 2020; Baran et al., 2022) been deemed as significant determinants of innovative output. By adding this more comprehensive list of controls we expect to approximate the true correlation more accurately. In model specification 3b, when *R&DIntensity* is the main variable of interest, we exclude this variable as a control. Following the baseline specification proceedings, we first run a regression with the full specification for each dependent variable and then include fixed effects for industry and year. All regressions also use robust standard errors clustered at the firm level. The full regression specifications follow:

$$\begin{aligned} Patentcount_{i,t} &= \alpha + \beta_1 DCS_{i,t} + \beta_2 R\&DIntensity_{i,t} + \beta_3 LnSales_{i,t} + \beta_4 ROA_{i,t} \\ &+ \beta_5 Leverage_{i,t} + \beta_6 Tobin's\,Q_{i,t} + \beta_7 CAPEXIntensity_{i,t} + \varepsilon_{i,t} \end{aligned} \tag{1b}$$

$$\begin{aligned} Patentcount/R\&D_{i,t} &= \alpha + \beta_1 DCS_{i,t} + \beta_2 R\&DIntensity_{i,t} + \beta_3 LnSales_{i,t} + \beta_4 ROA_{i,t} \\ &+ \beta_5 Leverage_{i,t} + \beta_6 Tobin's\,Q_{i,t} + \beta_7 CAPEXIntensity_{i,t} + \varepsilon_{i,t} \end{aligned} \tag{2b}$$

$$\begin{aligned} R\&DIntensity_{i,t} &= \alpha + \beta_1 DCS_{i,t} + \beta_2 LnSales_{i,t} + \beta_3 ROA_{i,t} + \beta_4 Leverage_{i,t} \\ &+ \beta_5 Tobin's\,Q_{i,t} + \beta_6 CAPEXIntensity_{i,t} + \varepsilon_{i,t} \end{aligned} \tag{3b}$$

4. Results

In the following section, we present the results of our tests. First, we examine the difference in innovation activity between dual- and single-class firms by looking at the number of patents. Second, we examine the difference in R&D efficiency, measured as the number of patents per million SEK of R&D expenditure, between dual- and single-class firms. Third, we examine the difference in R&D intensity between dual- and single-class firms, measured by R&D expenditure scaled by total company assets. We then continue to divide the full sample into subsamples and examine the relationship with innovation activity between these subsamples.

4.1. Innovation activity

Table 5 below shows the results of our baseline (1a) and full regression (1b) model for analyzing the difference in innovation activity, measured as the number of patents, between dual- and single-class firms.

Table 5

Regression results of Patentcount on dual-class share structure

This table reports the OLS estimates of the independent variables in the baseline and full model specifications, with *Patentcount* as the dependent variable. Columns (1) and (2) show the results for the baseline specification, whereas columns (3) and (4) show the results for the full specification. Columns (2) and (4) include year and industry (based on 2-digit GIC industry codes) fixed effects, whilst columns (1) and (3) do not. All regressions use robust standard errors clustered at firm level and are based on the full sample of 2441 firm-year observations. Due to missing values in *CAPEXIntensity* the regressions using the full model specifications use 2,324 observations. All variables have been winsorized at the 1% and 99% level. *, ** and *** indicates that the coefficient is statistically significant at 10%, 5% and 1% levels, respectively. The coefficients' t-statistics are reported in parenthesis below the estimates. The variables *R&D Intensity*, *Profitability*, *Leverage* and *CAPEXIntensity* are in percentage unit terms; hence, their coefficients correspond to the change in the dependent variable for a one percentage unit change.

	Baseline		Full	
	(1)	(2)	(3)	(4)
DCS	5.411**	4.434*	5.215**	4.518*
	(2.06)	(1.72)	(2.01)	(1.74)
R&DIntensity	0.751***	0.635***	0.617***	0.513***
	(3.25)	(3.48)	(3.15)	(3.32)
LnSales	5.622***	6.349***	7.282***	7.793***
	(3.62)	(3.49)	(3.62)	(3.52)
ROA			-0.225**	-0.245**
			(-2.45)	(-2.44)
TobinsQ			0.156	0.196*
			(1.52)	(1.70)
Leverage			-0.122	-0.086
			(-1.41)	(-1.17)
CAPEXIntensity			-0.539	-0.197
			(-1.40)	(-0.52)
Observations	2441	2441	2324	2324
Adj. R.sq	0.187	0.199	0.213	0.223
Year FE	No	Yes	No	Yes
Industry FE	No	Yes	No	Yes

In the regression results of *Patentcount* on dual-class share structure presented in Table 5, the coefficient for the *DCS* variable is positive and significant at the 5% or 10% level. This implies that dual-class firms on average file more patents that are subsequently granted than single-class firms. Column (1) show results from the baseline model without fixed effects. Within this model, the *DCS* coefficient is positive (5.411) and significant at 5%. The coefficients for the control variables, *LnSales* and *R&DIntensity*, are both positive and significant at 1%. The coefficient for *LnSales* implies that increasing sales by approximately 2.72[4] times is associated with a 5.622 higher annual *Patentcount*. While

[4] The value of Euler's number (2.71828)

the coefficient for *R&DIntensity* implies increasing R&D intensity by 1 percentage unit correlates with 0.751 higher annual *Patentcount*.

Column (3) shows results from the full model specification where additional control variables are introduced as results from the baseline regression in columns (1) and (2) may be influenced by omitted variable bias. The *DCS* coefficient is still positive (5.215) and significant at 5%, although it is somewhat lower than in the baseline model. The coefficient for *LnSales* increased from 5.622 to 7.282 and is still significant at 1%. Whilst also still being significant at 1%, the coefficient for *R&DIntensity* fell from 0.751 to 0.617. This hints at the existence of omitted variable bias in our results from our baseline model specification. The newly introduced control variables *TobinsQ*, *Leverage*, and *CAPEXIntensity* are generally not statistically significant. However, *ROA* is statistically significant and correlates negatively with *Patentcount*.

Column (4) shows results from the full model specification where year and industry fixed effects are introduced. The *DCS* coefficient remains positive (4.518) and is statistically significant at 10%. Even though the coefficient remains positive and significant, the level of statistical significance decreased when year and industry-fixed effects were introduced. This suggests that time or industry (or both) have a confounding effect on the choice of share class structure and *Patentcount*, leading to an upwards bias in the coefficient when not including the fixed effects. This can also be seen when comparing the results in columns (1) and (2), where the *DCS* coefficient is lower and have a smaller t-statistic when the year and industry-fixed effects are introduced to the baseline model. The results have a moderate economic significance; implying that firms with dual-class share structures on average file 4.518 more patents per year that are subsequently granted than firms with single-class share structures. These results are in line with our hypothesis, suggesting that dual-class share structures are positively associated with higher innovation activity.

4.2. R&D efficiency

Table 6 below shows the results of our baseline (2a) and full regression (2b) model for analyzing the difference in R&D efficiency, measured as the number of patents per million SEK R&D expenditure, between dual- and single-class firms.

Table 6

Regression results of Patentcount/R&D on dual-class share structure

This table reports the OLS estimates of the independent variables in the baseline and full model specifications, with *Patentcount/R&D* as the dependent variable. Columns (1) and (2) show the results for the baseline specification, whereas columns (3) and (4) show the results for the full specification. Columns (2) and (4) include year and industry (based on 2-digit GIC industry codes) fixed effects, whilst columns (1) and (3) do not. All regressions use robust standard errors clustered at firm level and are based on all firm-year observations with R&D expenditure larger than 0, with a sample size of 1,276. Due to missing values in *Patentcount/R&D* and *CAPEXIntensity* the regressions using the full model specifications have 1,240 observations. All variables have been winsorized at the 1% and 99% level. *, ** and *** indicates that the coefficient is statistically significant at 10%, 5% and 1% levels, respectively. The coefficients' t-statistics are reported in parenthesis below the estimates. The variables *R&DIntensity*, *ROA*, *Leverage* and *CAPEXIntensity* are in percentage unit terms; hence, their coefficients correspond to the change in the dependent variable for a one percentage unit change.

	Baseline		Full	
	(1)	(2)	(3)	(4)
DCS	0.039	0.036	0.025	0.022
	(1.65)	(1.46)	(1.58)	(1.42)
R&DIntensity	-0.004***	-0.004***	-0.005***	-0.005***
	(-3.11)	(-3.18)	(-3.13)	(-3.10)
LnSales	-0.024***	-0.022**	-0.009**	-0.007*
	(-2.63)	(-2.49)	(-2.26)	(-1.90)
ROA			-0.002**	-0.002**
			(-2.20)	(-2.05)
TobinsQ			0.002	0.001*
			(1.63)	(1.75)
Leverage			-0.001***	-0.002***
			(-2.67)	(-2.81)
CAPEXIntensity			0.000	0.000
			(-0.07)	(-0.14)
Observations	1,276	1,276	1,240	1,240
Adj. R.sq	0.078	0.082	0.078	0.079
Year FE	No	Yes	No	Yes
Industry FE	No	Yes	No	Yes

In the regression results of *Patentcount/R&D* on dual-class share structure the *DCS* coefficient is slightly positive but not statistically significant. The positive *DCS* coefficient points to firms with dual-class share structures producing more patents per million SEK of R&D expenditure. Column (1) shows results from the baseline model without fixed effects. Within this model the *DCS* coefficient is positive (0.039) but not statistically significant. The coefficients for the control variables, *LnSales* and *R&DIntensity*, are both negative and significant at 1%. The coefficient for *LnSales* implies that increasing sales by approximately 2.72[5] times is associated with 0.024 fewer

[5] The value of Euler's number (2.71828)

patents per million SEK of R&D expenditure. While the coefficient for *R&DIntensity* implies increasing R&D intensity by 1 percentage unit correlates with 0.004 fewer patents per million SEK of R&D expenditure.

Column (3) shows results from the full model specification where additional control variables are introduced as results from the baseline regression in columns (1) and (2) may have been influenced by omitted variable bias. The *DCS* coefficient is still positive (0.025) but not statistically significant, although it is lower than in the baseline model. The coefficient for *LnSales* increased from -0.024 to -0.009 and is significant at 5%. Whilst still being significant at 1%, the coefficient for *R&DIntensity* fell from -0.004 to -0.005, indicating that there exists omitted variable bias in our results from our baseline model specification. The newly introduced control variables *ROA*, *TobinsQ*, and *Leverage* are generally statistically significant, with *ROA* and *Leverage* having a negative correlation and *TobinsQ* having a slightly positive correlation with *Patentcount/R&D*. The last control variable *CAPEXIntensity* does not display any statistical significance.

Column (4) shows results from the full model where year and industry fixed effects are introduced. The *DCS* coefficient remains positive (0.022) but is still not statistically significant. Whilst not statistically significant, the results also have a low economic significance; implying that firms with dual-class share structures on average file 0.022 more patents for each million SEK invested in R&D per year compared to firms with single-class share structures. To infer the magnitude of the coefficient, one can relate it to the full sample mean R&D expenditure of SEK 404.94m, or to the mean of observations with R&D expenditure larger than 0, which is SEK 774.66m. As the results were neither statistically nor economically significant, they cannot show that dual-class share structures are positively associated with higher R&D efficiency and thus goes against our hypothesis. Since R&D reporting is not mandatory in Europe, many observations have been omitted due to missing data in the dependent variable. Therefore, one should be cautious about drawing conclusions from this regression as it may contain bias due to self-selection.

4.3. R&D intensity

Table 7 below shows the results of our baseline (3a) and full regression (3b) model for analyzing the difference in R&D Intensity, measured as R&D expenditure scaled by total assets, between dual- and single-class firms.

Table 7

Regression results of R&DIntensity on dual-class share structure

This table reports the OLS estimates of the independent variables in the baseline and full model specifications, with *R&DIntensity* as the dependent variable. Columns (1) and (2) show the results for the baseline specification, whereas columns (3) and (4) show the results for the full specification. Columns (2) and (4) include year and industry (based on 2-digit GIC industry codes) fixed effects, whilst columns (1) and (3) do not. All regressions use robust standard errors clustered at firm level and are based on the full sample of 2,441 firm-year observations. Due to missing values in *CAPEXIntensity* the regressions using the full model specifications have 2,324 observations. All variables have been winsorized at the 1% and 99% level. *, ** and *** indicates that the coefficient is statistically significant at 10%, 5% and 1% levels, respectively. The coefficients' t-statistics are reported in parenthesis below the estimates. The dependent variable and the control variables ROA, *Leverage*, and *CAPEXIntensity* are in percentage unit terms. Hence, the coefficient estimates correspond to percentage units change in *R&DIntensity*.

	Baseline		Full	
	(1)	(2)	(3)	(4)
DCS	-0.564	-0.775	-0.630	-0.831
	(-0.73)	(-1.05)	(-0.91)	(-1.24)
LnSales	-1.350***	-0.641***	-0.183	0.240
	(-5.70)	(-2.85)	(-0.92)	(1.22)
ROA			-0.233***	-0.214***
			(-4.95)	(-4.82)
TobinsQ			0.284***	0.278***
			(3.71)	(3.68)
Leverage			-0.113***	-0.098***
			(-4.53)	(-4.17)
CAPEXIntensity			-0.215**	-0.041
			(-2.55)	(-0.51)
Observations	2441	2441	2324	2324
Adj. R.sq	0.132	0.218	0.331	0.390
Year FE	No	Yes	No	Yes
Industry FE	No	Yes	No	Yes

In the regression results of *R&DIntensity* on dual-class share structure the *DCS* coefficient is slightly negative but not statistically significant. The negative coefficient points to firms with dual-class share structures investing less in R&D than single-class firms. Column (1) shows results from the baseline model without fixed effects. Within this model the *DCS* coefficient is negative (-0.564) but not statistically significant. The coefficient for the control variable *LnSales* is negative and statistically significant at 1%, implying that increased sales by 2.72[6] times are associated with 1.350 percentage units less *R&DIntensity*.

[6] The value of Euler's number (2.71828)

Column (3) shows results from the full model specification where additional control variables are introduced as results from the baseline regression in columns (1) and (2) may have been influenced by omitted variable bias. The *DCS* coefficient is still negative (-0.630) but not statistically significant. The *LnSales* coefficient increased from -1.350 to -0.183 but is no longer statistically significant. The newly introduced control variables *ROA*, *TobinsQ*, *Leverage*, and *CAPEXIntensity*, are all statistically significant, with *ROA*, *Leverage*, and *CAPEXIntensity* having a negative correlation with *R&DIntensity* whilst *TobinsQ* show a positive correlation.

Column (4) shows results from the full model where year and industry fixed effects are introduced. The *DCS* coefficient is slightly more negative (-0.831) but is still not statistically significant. Although still not statistically significant, the *LnSales* coefficient (0.240) increased and now shows a positive association with *R&DIntensity*. The remaining control variables are significant and point in the same direction as previously, except for *CAPEXIntensity* which is no longer significant.

The overall economic significance is moderate; implying that firms with dual-class share structures on average have 0.831 percentage units less *R&DIntensity* per year compared to firms with single-class share structures. To infer the magnitude of the coefficient, one can relate it to the full sample *R&DIntensity* mean of 4.03%. The results point in the direction of dual-class firms being less R&D intense than single-class firms, which is not in line with our hypothesis. However, since the results were not statistically significant, we cannot state anything. Since R&D reporting is not mandatory in Europe, many observations have 0 in the dependent variable due to missing data. Therefore, one should be cautious about drawing conclusions from this regression as the coefficient estimates. On the one hand, the estimates could be affected by downward bias, simply due to the mean *R&DIntensity* being lower when some companies do not report their R&D expenditure. On the other hand, any self-selection bias arising due to R&D reporting not being mandatory could lead to an over or underestimation of the variable coefficients. Nonetheless, coefficient estimates are likely biased.

4.4. Subsamples

Following previous research, we have separated the sample into different subsamples consisting of firms in high-tech vs low-tech industries, young vs old firms, and firms in industries with high- vs low-industry concentration. Table 8 below shows the results of the full regression model for analyzing the difference in innovation activity (1b), measured as the number of patents, between dual- and single-class firms divided into these subsamples.

Table 8

Subsample regression results of Patentcount on dual-class share structure

This table reports the subsamples OLS estimates of the independent variables in the full model specification, with *Patentcount* as the dependent variable. Column (1) show results for high-tech sectors while column (2) show low-tech sectors. Column (3) show results for young firms (10 years or less since IPO) while column (4) show results for old firms (more than 10 years since IPO). Column (5) shows results for low industry concentration (below sample median) while column (6) shows high industry concentration (above sample median). All regressions include year and industry (based on 2-digit GIC industry codes) fixed effects and use robust standard errors clustered at firm level. All variables have been winsorized at the 1% and 99% level. *, ** and *** indicates that the coefficient is statistically significant at 10%, 5% and 1% levels, respectively. The coefficients' t-statistics are reported in parenthesis below the estimates. The variables *R&DIntensity*, *ROA*, *Leverage* and *CAPEXIntensity* are in percentage unit terms; hence, their coefficients correspond to the change in the dependent variable for a one percentage unit change.

	High-tech vs. low-tech		Young vs. old		Industry concentration	
	(1)	(2)	(3)	(4)	(5)	(6)
DCS	3.070	4.877	3.159	3.389	2.716	6.173*
	(1.00)	(1.31)	(1.08)	(0.96)	(0.68)	(1.71)
R&DIntensity	0.250*	1.649**	0.134**	0.972***	0.418**	0.583**
	(1.86)	(2.45)	(2.11)	(3.13)	(2.37)	(2.52)
LnSales	7.080	8.807***	2.106**	10.304***	7.467***	8.270**
	(1.48)	(3.62)	(2.02)	(3.57)	(2.94)	(2.20)
ROA	-0.260	-0.129	-0.077*	-0.185	-0.261*	-0.240*
	(-1.26)	(-0.71)	(-1.69)	(-1.37)	(-1.87)	(-1.76)
TobinsQ	-0.101	0.332	0.036	-0.058	0.335*	0.142
	(-0.66)	(1.55)	(0.78)	(-0.22)	(1.82)	(0.91)
Leverage	-0.293	0.057	-0.071*	0.051	-0.069	-0.121
	(-1.43)	(0.58)	(-1.80)	(0.47)	(-0.68)	(-1.49)
CAPEXIntensity	-0.204	-0.282	-0.163	-0.276	0.463	-0.606
	(-0.43)	(-0.59)	(-1.11)	(-0.42)	(0.63)	(-1.24)
Observations	930	1394	889	1431	1137	1187
Adj. R.sq	0.227	0.245	0.104	0.277	0.187	0.269
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes

Columns (1) and (2) in Table 8 show the regression results of *Patentcount* on dual-class share structure when separating the full sample into high-tech and low-tech subsamples. Both subsamples show a positive but not significant *DCS* coefficient. Column (1) show results for the high-tech subsample. For this sample, the *DCS* coefficient is 3.070 which is lower compared to the full sample (4.518). Column (2) shows results for the low-tech subsample. The *DCS* coefficient is 4.877, which is higher than for both the high-tech subsample (3.070) and the full sample (4.518). Although not statistically significant, the results imply that the association between *Patentcount* and dual-class share structures is more prevalent in low-tech industries. Worth noting is that both subsamples have lacking statistical significance in most variables, especially the high-tech subsample. Furthermore, the high-tech subsample has much fewer observations (930) compared to the low-tech subsample (1394), which may contribute to the lack of significance.

Columns (3) and (4) show the regression results when dividing the full sample into two age buckets depending on the time since IPO. Column (3) shows results for the young subsample (10 years or less since IPO), and corresponding results for the old sample (more than 10 years since IPO) is shown in column (4). Both subsamples have positive but not statistically significant *DCS* coefficients. The *DCS* coefficient for the young sample is somewhat lower (3.159) compared to the old subsample (3.389). The coefficients for *LnSales* and *R&DIntensity* are positive and statistically significant for both subsamples, but the magnitude of the coefficients is much larger for the old sample. The *LnSales* coefficient is 2.106 for young firms compared to 10.304 for old firms, and the *R&DIntensity* coefficient is 0.134 for young firms compared to 0.972 for old firms. The remaining control variables are generally not significant, except for *Leverage* and *ROA* which display a negative association with *Patentcount* for young firms with dual-share class structure. The economic significance of these results is low; they are implying that young dual-class firms file 3.159 more patents than young single-class firms, and old dual-class firms file 3.389 more patents than old single-class firms. Although not statistically nor economically significant, the results point in the direction that the positive association between Patentcount and dual-class share structures is more prevalent in old firms.

Columns (5) and (6) show the regression results of *Patentcount* on dual-class share structure when separating the full sample into high- vs low industry concentration. Column (5) shows results for the subsample with low industry concentration. For this subsample, the *DCS* coefficient is positive (2.716) but not significant. Column (6) shows results for the subsample with high industry concentration. The *DCS* coefficient for this subsample is 6.173 and significant at 10%, meaning that firms with dual-class share structures within this subsample produce 6.173 more patents than single-class firms per year. The coefficients for the control variables, *LnSales* and *R&DIntensity*, are both positive and significant at 1% or 5%. The remaining control variables are generally not significant, except for *ROA* which displays a negative association with *Patentcount* for both subsamples. Overall, the results imply that the association between *Patentcount* and dual-class share structures is more prevalent when industry concentration is high.

5. Robustness checks

In the following section, we present the results from several robustness tests performed on our regressions to examine whether the results may be biased by controllable factors. First, we test the robustness of the results concerning the difference in innovation activity, measured by the number of patents, between dual- and single-class (presented in section 4.1). Second, we test the robustness of the results concerning the difference in R&D efficiency, measured as the number of patents per million SEK of R&D expenditure, between dual- and single-class firms (presented in section 4.2). Third, we test the robustness of the results concerning differences in R&D intensity, measured by R&D expenditure scaled by total company assets, between dual- and single-class firms (presented in section 4.3).

5.1. Innovation activity

Table 9 below shows the results from our robustness checks for the results concerning the difference in innovation activity, measured by the number of patents, between dual- and single-class (presented in section 4.1).

Table 9

Regression results for Patentcount on dual-class share structure

This table reports the OLS estimates for the independent variables from the regressions employed as robustness checks for the results presented in section 4.1. All the regressions have *Patentcount* as the dependent variable, if not stated otherwise, and use the full model specification with year and industry fixed effects. Column (1) reports the results obtained when excluding the outliers Ericsson, Volvo and SKF. Column (2) has the natural logarithm of *Patentcount* (*LnPatentcount)* as the dependent variable. Column (3) reports the results from a subsample of observations pertaining to firms with recorded patent filings during the sample period. Column (4) reports the results from a subsample pertaining to firms with recorded patent filings during the sample period excluding the outliers Ericsson, Volvo and SKF. All variables have been winsorized at the 1% and 99% level. *, ** and *** indicates that the coefficient is statistically significant at 10%, 5% and 1% levels, respectively. The coefficients' t-statistics are reported in parenthesis below the estimates. The variables *R&DIntensity*, *ROA*, *Leverage* and *CAPEXIntensity* are presented in percentage unit terms.

	(1)	(2)	(3)	(4)
DCS	1.303	0.112	7.196*	2.135
	(0.66)	(1.01)	(1.67)	(0.62)
R&DIntensity	0.313***	0.035***	0.483**	0.318***
	(3.76)	(4.87)	(2.43)	(2.64)
LnSales	4.119***	0.348***	10.990***	5.881***
	(3.57)	(5.94)	(3.75)	(3.69)
ROA	-0.099*	-0.007*	-0.403***	-0.186**
	(-1.74)	(-1.82)	(-2.60)	(-1.98)
TobinsQ	0.136**	0.013***	0.020	0.095
	(2.15)	(2.98)	(0.09)	(0.84)
Leverage	-0.049	-0.006*	-0.170	-0.081
	(-1.02)	(-1.90)	(-1.07)	(-0.90)
CAPEXIntensity	-0.188	-0.020	-0.234	-0.468
	(-0.84)	(-1.09)	(-0.26)	(-0.84)
Observations	2291	2324	1212	1179
Adj. R.sq	0.145	0.286	0.287	0.181
Year FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes

In section 3.4 we highlighted that Ericsson, Volvo, and SKF are large outliers in terms of *Patentcount*, having 14%, 13%, and 12% of the total patent filings in our full sample respectively. In contrast, the fourth largest patentee accounted for 5% of the total *Patentcount*. Since these outliers cumulatively constitute 38% of our patent filings in the full sample, and they all have dual-share class structures for the whole sample period, we tested if our results in section 4.1 would be robust to a subsample that excludes these companies. Thus, we regress *Patentcount* on our full model specification, with year and industry fixed effects, on a sample that excludes observations from Ericsson, Volvo, and SKF (results found in Table 9, Column (1)). From this, we first find that the *DCS* coefficient is drastically lower. Whilst this was to some degree expected, the coefficient fell by 71% (from 4.518 to 1.303), while the total *Patentcount* was only 38% lower in this sample compared to the full sample. More importantly, the *DCS* coefficient is no longer statistically significant at the 10% level.

As mentioned in section 3.4, there exists right skewness in the *Patentcount* variable. To check if our results are robust when mitigating any issues and bias arising from this, we use the natural logarithm of *Patentcount (LnPatentcount)* as the dependent variable and regress it on our full model specification with industry and year-fixed effects (results found in Table 9, Column (2)). The *DCS* coefficient implies that having a dual-share class structure is associated with an 11.2% higher annual *Patentcount*. Whilst the implied economic significance of this variable is high, it is statistically insignificant.

Due to this paper's focus on innovation and using patents as a measure of innovation input, one of the robustness checks we employ is only using a subsample limited to observations of firms that have filed for a patent during the sample period 2009-2019. Using this subsample, we regress *Patentcount* on our full model specification with industry and year fixed effects (results found in Table 9, Column (3)). We can see that the *DCS* coefficient is 7.196, which is higher than our estimate when using the full sample (4.518). This is expected since the average *Patentcount* for the observations in this subsample naturally is higher than in the original sample. Like our results using the full sample, the *DCS* coefficient is also significant at 10%, however with a slightly lower t-statistic (1.67 compared to 1.74). Further, the coefficient for *R&DIntensity* in this robustness test is slightly lower (0.483 compared to 0.513) and only significant at the 5% level, instead of 1%, indicating that this measure is a smaller determinant of *Patentcount* for patenting companies. Lastly, the coefficient for *LnSales* is larger (10.990 compared to 7.793) and still significant at the 1% level. Arguably, these estimates are more relevant since non-patenting firms are excluded, and we thus capture the firms for which patents are a relevant part of their business. Some companies may not focus on innovation whatsoever, and one should therefore not expect that these companies' share structures have any association with innovation.

Lastly, we run a regression with only patenting firms whilst excluding the outliers Ericsson, Volvo, and SKF (results found in Table 9, Column (4)). We can see that the *DCS* coefficient is now considerably lower (2.135) and no longer statistically significant.

5.2. R&D efficiency

Table 10 below shows the results from our robustness checks for the results concerning the difference in R&D efficiency, measured as the number of patents per million SEK of R&D expenditure, between dual- and single-class firms (presented in section 4.2).

Table 10

Regression results for Patentcount/R&D on dual-class share structure

This table reports the OLS estimates for the independent variables from the regressions employed as robustness checks for the results presented in section 4.2. All the regressions use *Patentcount/R&D* as the dependent variable, if not stated otherwise, and the full model specifications with year and industry fixed effects. Column (1) reports the results obtained when excluding the outliers Ericsson, Volvo and SKF. Column (2) has the natural logarithm of *Patentcount/R&D* (*LnPatentcount/R&D)* as the dependent variable. Column (3) reports the results from a subsample of observations pertaining to firms with recorded patent filings during the sample period. Column (4) reports the results from a subsample pertaining to firms with recorded patent filings during the sample period excluding the outliers Ericsson, Volvo and SKF. All variables have been winsorized at the 1% and 99% level. *, ** and *** indicates that the coefficient is statistically significant at 10%, 5% and 1% levels, respectively. The coefficients' t-statistics are reported in parenthesis below the estimates. The variables *ROA*, *Leverage* and *CAPEXIntensity* are presented in percentage unit terms.

	(1)	(2)	(3)	(4)
DCS	0.020	0.013	0.029	0.026
	(1.31)	(1.31)	(1.47)	(1.35)
R&DIntensity	-0.005***	-0.003***	-0.008***	-0.008***
	(-3.12)	(-3.27)	(-3.51)	(-3.52)
LnSales	-0.009**	-0.004	-0.013***	-0.016
	(-2.30)	(-1.63)	(-2.71)	(-3.00)
ROA	-0.002**	-0.001**	-0.003**	-0.003**
	(-1.97)	(-2.06)	(-2.43)	(-2.34)
TobinsQ	0.001*	0.001*	0.002	0.002
	(1.75)	(1.80)	(1.28)	(1.33)
Leverage	-0.001***	-0.001***	-0.002***	-0.002***
	(-2.75)	(-2.95)	(-2.89)	(-2.82)
CAPEXIntensity	-0.000	0.000	-0.003	-0.003
	(-0.11)	(0.02)	(-0.89)	(-0.91)
Observations	1,207	1,240	925	892
Adj. R.sq	0.081	0.076	0.133	0.137
Year FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes

Like our results pertaining to *Patentcount*, we employ the same robustness tests for *Patentcount/R&D*. We test if our results are robust when excluding observations of Ericsson, Volvo, and SKF; when transforming the dependent variable (*Patentcount/R&D*) by using the natural logarithm instead, to account for right skewness in our data; when using a subsample of observations from firms which filed for patent during our sample period; and when excluding the outliers Ericsson, Volvo and SKF from the subsample of firms which filed for patent during our sample period. The results for each test are found in Table 10 Columns (1), (2), (3), and (4) respectively. Like our initial results in section 4.2 (Table 6, Column (4)) all our robustness test yield statistically insignificant coefficients for the *DCS* variable and of similar magnitude.

5.3. R&D intensity

Table 11 below shows the results from our robustness checks for the results concerning the difference in R&D intensity, measured by R&D expenditure scaled by total company assets, between dual- and single-class firms (presented in section 4.3).

Table 11

Regression results for R&DIntensity on dual-class share structure

This table reports the OLS estimates for the independent variables from the regressions employed as robustness checks for the results presented in section 4.3. All regressions have R&DIntensity as the dependent variable, if not stated otherwise, and use the full model specification with year and industry fixed effects. Column (1) reports the results obtained when excluding the outliers Ericsson, Volvo and SKF. Column (2) has the natural logarithm of R&DIntensity (*LnR&DIntensity)* as the dependent variable. Column (3) reports the results from a subsample of observations pertaining to firms with reported R&D expenditure larger than 0 during the sample period. Column (4) reports the results from a subsample pertaining to firms with reported R&D expenditure larger than 0 during the sample period excluding the outliers Ericsson, Volvo and SKF. All variables have been winsorized at the 1% and 99% level. *, ** and *** indicates that the coefficient is statistically significant at 10%, 5% and 1% levels, respectively. The coefficients' t-statistics are reported in parenthesis below the estimates. The variables *R&DIntensity*, *ROA, Leverage* and *CAPEXIntensity* are presented in percentage unit terms.

	(1)	(2)	(3)	(4)
DCS	-0.905	-0.734	-2.104**	-2.156**
	(-1.35)	(-1.24)	(-2.21)	(-2.27)
LnSales	0.139	0.197	0.417	0.311
	(0.69)	(1.14)	(1.63)	(1.14)
ROA	-0.209***	-0.174***	-0.223***	-0.218***
	(-4.67)	(-4.79)	(-4.87)	(-4.70)
TobinsQ	0.275***	0.234***	0.359***	0.360***
	(3.64)	(3.62)	(3.51)	(3.53)
Leverage	-0.096***	-0.085***	-0.136***	-0.134***
	(-4.05)	(-4.24)	(-4.20)	(-4.09)
CAPEXIntensity	-0.038	-0.042	-0.004	0.001
	(-0.48)	(-0.60)	(-0.04)	(0.00)
Observations	2291	2324	1583	1,550
Adj. R.sq	0.390	0.385	0.419	0.419
Year FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes

For *R&DIntensity*, we test if our results are robust when excluding observations of Ericsson, Volvo, and SKF, and when transforming the dependent variable *R&DIntensity* by using the natural logarithm instead, to account for right skewness in our data (results found in Table 11 Column (1) and (2) respectively). Further, we run a regression with a subsample of observations of firms that have reported positive R&D expenditure during our sample period, with results presented in Table 11 Column (3). Lastly, we run a regression with the subsample of observations of firms that have reported positive R&D

expenditure excluding Ericsson, Volvo, and SKF, results presented in Column (4). For this innovation measure, our results are robust to the first two tests, as the *DCS* coefficients in Columns (1) and (2) are statistically insignificant and have a similar magnitude to our initial result. However, we see contradicting results in our third and fourth tests that pertain to the tests only including firms with positive R&D expenditure during our sample period. For these tests, the *DCS* coefficient is more negative than the initial results (-0.831) and significant at 5%. Results in Column (3) imply that firms with dual-class share structures on average have 2.104 percentage units less *R&DIntensity* per year compared to firms with single-class share structures. The results point in the direction of dual-class firms being less R&D intense than single-class firms, which is not in line with our hypothesis. However, as previously mentioned in section 4.3, coefficient estimates are likely biased due to missing R&D data, and one should be careful when interpreting these results.

6. Discussion

The results from all examined innovations measures generally show low levels of statistical significance and therefore need to be interpreted with caution. Starting with innovation input, measured as R&D intensity, results show moderate economic effects but no statistical significance. The results suggest that dual-class firms are less R&D intense than single-class firms, which goes against our expectations while also not being directionally consistent with results from remaining innovation measures. Relevant robustness tests yield contradicting results; with the first two further supporting the initial insignificant result, while the other ones show significant results indicating a negative association between dual-class shares and R&D intensity. The third regression used a subsample consisting of firms that reported positive R&D expenditure during the sample period. This may have resulted in a better fit of our model since most observations with R&D expenditure equal to zero originally had missing values, as we replaced missing values with zeros following previous studies. Including these observations may have introduced unnecessary noise in our regression and adversely affected estimation precision. However, we are cautious about drawing any conclusions based on this subsample since it is likely affected by self-selection bias. Since R&D expenditure is not mandatory to report, one possibility is that firms with higher R&D expenditure are more likely to report. Furthermore, since the quality of financial reports is higher for dual-class firms (Solomon et al., 2020), these companies might be more inclined to report R&D expenditures than their single-class counterparts regardless of if the R&D expenditure is low, which could cause a downward bias in these coefficient estimates. The reasoning behind this is that controlling owners in dual-class firms may provide investors with higher-quality information in exchange for superior voting rights.

Results on R&D efficiency show low economic effects with no statistical significance. However, the direction of the coefficient is in line with our hypothesis, pointing towards dual-class firms being somewhat more efficient in their R&D usage. The results from the robustness further support our original results. However, due to the lack of statistical significance, we refrain from drawing any conclusions regarding these results.

Regarding the results on innovation activity, measured by the number of patents filings which were ultimately granted, the initial findings show moderate economic effects that are statistically significant. This points to dual-class share structures being associated with a larger amount of patents filings. However, the results were only significant at the 10% level. When removing specific outliers accounting for many patents, more specifically Ericsson, Volvo, and SKF, the results were no longer significant. When using the natural logarithm of patent counts instead of patent counts, the results once again lost their statistical significance. On the other hand, when only including patenting firms in the regression the results were shown to be robust, but when excluding outliers from this sample the test once again lost the statistical significance. Overall, these tests fail to find any robust results for dual-class share structure on innovation activity, measured by the number of patents. Worth noting however is that although the results were not consistently statistically significant, they were directionally consistent in our variable of interest.

We further investigate the possibility of the positive association between dual-class share structure and innovation activity only being prevalent in certain subsamples. Besides the results regarding industry concentration, no coefficients for the dual-class share structure were statistically significant. The subsample with high industry concentration displayed both economic and statistical significance, suggesting that dual-class firms within these industries are positively associated with the number of patents, which is in line with our expectations. The results support the view presented by Li et al. (2019) that the ability of insiders to act quickly and decisively to capture innovative opportunities may be more beneficial when there is high industry competition. Even though these results indicate that dual-class share structure may benefit companies in such industries in terms of innovative output, we are cautious about drawing any conclusions from these results given the relatively low level of statistical significance, the lack of significance for the low concentration sample, as well as the weak robustness in our main results. As previously mentioned, the other subsamples did not show any statistically significant results. Putting this aside, when economically interpreting the dual-class coefficients for these subsamples, they contradict the results from previous studies where the positive association between dual-class firms and innovation was concentrated in high-tech industries and young firms.

Overall, we have weak evidence of dual-class share structures being beneficial for the number of patents, mostly for companies in industries with high concentration. These results are somewhat in line with Baran et al. (2022) study on the US market that showed a positive association between dual-class shares and the number of patents as well as R&D efficiency, which was found to be concentrated in highly competitive industries. However, contrary to Baran et al. (2022), after conducting several robustness tests we conclude that we cannot find any robust evidence. One of the main differences between our studies is that Baran et al. (2022) distinguished the *disproportionate insider control* mechanism by matching dual-class firms with single-class firms possessing similar *takeover protection*. We were however expecting to see the same results in our study since the *takeover protection* mechanism may not be as important in Sweden (Skog, 2004). Another difference is that Baran et al. (2022) controlled for *specific insiders*, which is something we did not control for. Their results were however significant before the introduction of this control as well, so it should not be the main reason for our results lacking significance. Although not in line with our hypothesis, there are some similarities with Cao et al. (2020) results, where they found no association between dual-class share structure and the number of patents. One potential reason for our results being more in line with Cao et al. (2020) could be that the *takeover protection* mechanism does play a part in the Swedish market, contrary to Skog (2004) findings. Even though the expected positive association was not found, results from this study may suggest that the dual-class share structure is at least not negatively associated with the number of patents, which opposes the agency cost view and is in line with Cao et al. (2020) argumentation.

There are several more reasons why our results may not be consistent with previous research, one being due to our study focusing on the Swedish market instead of the US market. This is in line with our hypotheses formulation where we argued that the two markets are different regarding shareholder protection and takeover climate. There might however be other characteristics in which the two markets differ. Contrary to the dataset used by Cao et al. (2020), in our sample, companies in low-tech industries had more patent filings than companies in high-tech industries. This might further indicate that the Swedish economy is underlined by different market characteristics than the US market, which might entail that the relationship between dual-class share structure also is different between the two economies. Although the original argument that the Swedish and US markets are different stands firm, the initial reasoning that the positive influences of dual-class shares may be further reinforced by Sweden's strong minority shareholder protection and takeover climate may not tell the whole story. There are of course multiple factors that can play a part in the two markets having differing results and it is difficult to isolate the influence of one specific characteristic.

Another potential explanation for why our results may differ from previous literature is our study has a smaller sample size. Baran et al. (2022) have a sample size of 5,204 compared to our sample of 2,441 observations. The DCS coefficients for our different measures of innovation, besides R&D Intensity, were directionally consistent, being positive for the number of patents and R&D efficiency across the different model specifications and robustness tests. For these two innovation measures, it is possible that our estimates captured the right direction and approximate correlations between having a dual-class share structure and the different innovation measures, whilst not being statistically significant due to low estimate precisions resulting from a small sample size. To achieve a larger sample size in this study we would have had to include a longer period which would mean overlapping with the financial crisis in 2008. Since including this period could make the results difficult to interpret as they may be affected by abnormal market conditions, we decided against it.

Since both Cao et al. (2020) and Baran et al. (2022) studied periods before the global financial crisis, an alternative explanation to why our findings may not be comparable with their results is that the relationship between our innovation measures and a dual-class share structure has changed since the financial crisis of 2008. For instance, both investors and managers may have become more risk averse after the global financial crisis, discouraging risky investments into innovation and thus innovation output as well. This argument does however not reconcile with the trend of increasing appetite for innovation presented by PwC's market research (2013).

Furthermore, previous studies have used a lagged patent count as a dependent variable, which is reasonable since patent filings – an innovation output – probably has a time lag relative to its innovation input. However, we chose not to use a similar model specification due to it reducing our already small sample size, since we would lose one observation per firm for each year lagged. Nonetheless, using a different model specification can naturally be one of the causes of our results being different from previous studies. Another difference in our model specification pertains to the simplification that we assume dual-class shares equal disproportionate insider control. This does not have to be the case as companies can have dual-class share structures without achieving insider control. Such companies would not fully realize the effect of the dual-class share structure. This would diminish the significance, economically and statistically of our dual-class coefficient. Previous studies have instead used the wedge between votes and capital which better captures the disproportionate insider control mechanism, although this measure also has its flaws; even though it captures the differential voting rights and that it is common for insiders to control these superior voting shares, that does not have to be the case.

7. Conclusions and Limitations

7.1. Conclusions

This thesis aims to investigate the association between dual-class share structures and innovation among Swedish firms. The analysis is based on a sample of 2,441 firm-year observations of Swedish firms listed on Nasdaq Stockholm and First North Growth Market during the period 2009-2019. We hypothesize that dual-class share structures are positively associated with innovation, measured by the number of patents, R&D efficiency, and R&D intensity. Contrary to our hypothesis we find that dual-class shares have no significant association with any of the examined innovation measures. However, we notice a possibly positive association between dual-class shares and the number of patents in high-concentration industries. When economically interpreting the results, disregarding the lack of statistical significance, they imply that dual-class shares are positively associated with the number of patents and R&D efficiency whilst being negatively associated with R&D intensity.

7.2. Limitations and future research

Although this paper provides some clarity regarding the relationship between dual-class share structure and innovation in Sweden, the study has several limitations which we proceed to highlight below.

One concern is that the study may be subject to endogeneity issues due to omitted variables. As such we would fail to capture the true association between dual-class shares and innovation. For example, innovative management could be an omitted variable, which goes in line with Baran et al. (2022) argument regarding the positive effect of dual-class shares for innovation being conditional on innovative insiders. High-quality managers tend to have a larger number of anti-takeover provisions compared to low-quality managers (Chemmanur et al., (2011), which would make them more likely to adopt a dual-class share structure. It is also likely that innovative managers would engage in successful innovation activities that result in innovative output. Thus, the dual-class share structure could be positively correlated with the firm’s innovation, which could be the reason for this study sometimes finding a positive correlation. The omitted variable bias could of course be mitigated by improving the model specification. As such, we encourage further studies to incorporate additional significant determinants of innovation, for instance, management characteristics.

Another related concern is that our estimates might be biased due to the self-selection of dual-class status. If self-selection does occur and is not controlled for in our models, this naturally has a detrimental effect on our study and makes our results less reliable, since the obtained estimates would not reflect the true relationship between our dependent variables and variable of interest. In previous literature. this has been solved by using propensity score matching. This study does not adopt a matched sample, so the dual- and single-class firms may not be directly comparable. This is further reinforced when looking at descriptive statistics of our sample in Table 1A, where it is displayed that dual- and single-class firms are significantly different with regards to R*&DIntensity*, *ROA*, *LnSales*, *TobinsQ,* and *CAPEXIntensity*. Future studies examining the Swedish market could try to adopt a matched sample to better control for these differences. Alternatively, one could use instrumental variables to exclude any bias stemming from self-selection.

Moreover, by only using patent counts as a measure of innovation, this study fails to capture the quality of innovation as well as separate ground-breaking innovations from others. Future research could expand this study to include patent citations as a measure of innovation quality. Furthermore, this study only includes Swedish firms and their Swedish subsidiaries, which means patents belonging to foreign subsidiaries are not accounted for. This may result in a less comparable sample as firms may have differing patenting strategies and some companies in the sample have a much stronger international presence than others. Other potential control variables adopted in previous studies that may contribute to more reliable results are age, antitakeover protection, wedge, and specific insiders, however, due to information access and time limitations this was not deemed feasible.

Another limitation is our rather small sample size of 2,441 observations, compared to for example Baran et al. (2022) that have a sample size of 5,204 observations. The small sample size could be the reason for us failing to find, or only finding weak, statistical significance. As such, future research could study a larger sample, either by studying a larger market, such as the Nordic market, or having a larger sample period. However, a caveat of expanding the sample period is including observations from the financial crisis and potentially before the crisis as well. Studying such a sample may run into the issue of the results not being applicable to neither the period before, during, or after the global financial crisis. Moreover, if the true relationship between a company having a dual-share class structure and their innovation input is fundamentally different between the above-mentioned periods, such a sample period may simply obfuscate the results.

Our study did not find any statistically significant results, and as such, establishing whether there is a causal relationship between having a dual-class share structure and innovation would not be applicable to this paper. However, to test for a causal relationship between share class structure and innovation, future studies could employ instrumental variables in their regressions.

8. References

Adams, R., & Ferreira, D. (2008). One share-one vote: The empirical evidence. *Review of Finance*, 12(1), 51–91.

Amess, K., Stiebale, J., & Wright, M. (2015). The impact of private equity on firms' patenting activity. *European Economic Review*, 86, 147–160.

Atanassov, J. (2013). Do Hostile Takeovers Stifle Innovation? Evidence from Antitakeover Legislation and Corporate Patenting: Takeovers and Innovation. *The Journal of Finance*, 68(3), 1097–1131.

Baran, L., Forst, A., Via, M.T., (2022). Dual Class Share Structure and Innovation. *The Journal of Financial Research*, 46, 169-202.

Bebchuk, L., Kraakman, R. &Triantis, G., (2000). Stock Pyramids, Cross-Ownership, and Dual Class Equity: The Mechanisms and Agency Costs of Separating Control from Cash-Flow Rights. *Concentrated Corporate Ownership*, 10, 295-318.

Bernstein, S. (2015). Does going public affect innovation? *The Journal of Finance*, 70(4), 1365–1403.

Cao, X., Leng, T., Goh, J., & Malatesta, P. (2020). The innovation effect of dual-class shares: New evidence from US firms. *Economic Modelling*, 91, 347–357.

Chemmanur, T.J., Paeglis, I. & Simonyan, K. (2011). Management Quality and Antitakeover Provisions. *Journal of Law and Economics*, 54, 651–692.

Chemmanur, T. J., & Jiao, Y. (2012). Dual-class IPOs: A theoretical analysis. *Journal of Banking & Finance*, 36(1), 305–319.

Cheng, W., Mpundu, H. & Wan, H. (2020). Investment efficiency: Dual-class vs Single-class firms. *Global Finance Journal*, 45, 100477.

Coffee, J. (2001). Do Norms Matter? A Cross-Country Examination of the Private Benefits of Control. Columbia Law School Working Paper 183.

Committee on Capital Markets Regulation (2020). The Rise of Dual Class Shares: Regulation and Implications. Retrieved May 4, 2023, from https://www.capmktsreg.org/wp-content/uploads/2020/04/The-Rise-of-Dual-Class-Shares-04.08.20-1.pdf.

DeAngelo, H. & DeAngelo, L., (1985). Managerial ownership of voting rights: a study of public corporations with dual-classes of common stock. *Journal of Financial Economics*, 14, 33–69.

Dyck, A., & Zingales, L., (2004). Private Benefits of Control: An International Comparison. *The Journal of Finance*, 59, 537-600.

Ferreira, D., Manso, G., & Silva, A.C. (2014). Incentives to innovate and the decision to go public or private. *Review of Financial Studies*, 27(1), 256–300.

Gompers, P. A., Ishii, J., & Metrick, A. (2010). Extreme governance: An analysis of dual-class firms in the United States. *Review of Financial Studies*, 23(3), 1051–1088.

Graham, J., Campell H., & Rajgopal, S. (2005). The economic implications of corporate financial reporting. *Journal of Accounting and Economics*, 40, 3-37.

Griliches, Z., Pakes, A. & Hall, B. (1986). The Value of Patents as Indicators of Inventive Activity. Harvard University Working paper.

Grossman, S. & Hart, O. (1988) One share-one vote and the market for corporate control. *Journal of Financial Economics*, 20, 175–202.

Hall, B.H, & Ziedonis, R.H. (2001). The patent paradox revisited: an empirical study of patenting in the US semiconductor industry, 1979-1995. *The Rand Journal of Economics*, 32, 101-128.

Holmén, M., & Knopf, J., (2004). Minority Shareholder Protections and the Private Benefits of Control for Swedish Mergers. *Journal of Financial and Quantitative Analysis*, 39, 167-191.

Holmström, B. (1989). Agency costs and innovation. *Journal of Economic Behavior and Organization*, 12, 305–327.

Howell, J. W. (2017). The survival of the U.S. dual-class share structure. *Journal of Corporate Finance*, 44, 440–450.

Hughes, J. (2015). Hong Kong regulator feels heat over decision on dual-class shares. *Financial Times*, March 24. Retrieved May 5, 2023, from https://www.ft.com/content/8429f686-d203-11e4-b66d-00144feab7de.

Jensen, M. C., & Meckling, W. H. (1976). Theory of the firm: Managerial behavior, agency costs and ownership structure. *Journal of Financial Economics*, 3(4), 305-360.

Johnson, S., La Porta, R., Lopez-de-Silanes, F. & Shleifer, A. (2000). Tunneling. *American Economic Review*, 90, 22–27.

Jordan, B. D., Kim, S., & Liu, M. H. (2016). Growth opportunities, short-term market pressure, and dual-class share structure. *Journal of Corporate Finance*, 41, 304–328.

Jönsson, A. (2023). Lundbergbolagets makt över telekomjätten hotas. *Dagens Industri*, April 5. Retrieved May 5, 2023, from https://www.di.se/analys/lundbergbolagets-makt-over-telekomjatten-hotas/.

Kile, C. & Phillips, M. (2009). Using industry classification codes to sample high-technology firms: Analysis and recommendations. *Journal of Accounting, Auditing & Finance*, 24, 35-58.

La Porta, R., Lopez-de-Silanes, Florencio & Shleifer, A. (1999). Corporate Ownership around the world. *Journal of Finance,* 54(2), 471-517.

Li, M., Lu, Y., & Phillips, G. M. (2019). CEOs and the product market: When are powerful CEOs beneficial*? Journal of Financial and Quantitative Analysis*, 54(6), 2295–2326.

Lidman, E. & Skog, R. (2022). London allowing dual class premium listings: A Swedish comment. *Journal of Corporate Law Studies*, 22, 83-114.

Manso, G. (2011). Motivating innovation. *The Journal of Finance*, 66(5), 1823–1860.

Masulis, R. W., Wang, C., & Xie, F. (2009). Agency problems at dual-class companies. *The Journal of Finance,* 64(4), 1697–1727.

PwC (2013). Unleashing the power of innovation. Retrieved May 3, 2023, from https://www.pwc.com/im/en/assets/document/unleashing_the_power_of_innovation.pdf

Rex, M. (2022). Mäktig rådgivare till attack – maktbolag i skottgluggen, *Dagens Industri*, December 9. Retrieved May 5, 2023, from https://www.di.se/nyheter/maktig-radgivare-till-attack-maktbolag-i-skottgluggen/.

Seligman, J. (1986). Equal Protection in Shareholder Voting Rights: The One-Share-One-Vote Controversy. *George Washington Law Review*, 54, 687-724.

Skog R, (2004). The European Union's Proposed Takeover Directive, the "Breakthrough" Rule, and the Swedish System of Dual Class Common Stock. *Scandinavian Studies in Law*, 45, 393-306.

Solomon, D., Palas, R. & Baranes, A. (2020). The Quality of Information Provided by Dual-Class Firms. *American business law journal*, 57(3), 443-486.

Solow, R.M., (1957). Technical change and the aggregate production function. *The Review of Economics and Statistics*, 39(3), 312-320.

Yermack, D. (2006). Flights of fancy: Corporate jets, CEO perquisites, and inferior shareholder returns. *Journal of Financial Economics*, 80, 211–242.

Appendix

Table 12

Descriptive statistics for full sample

The table reports summary statistics for the variables constructed from the sample of public Swedish firms from 2009-2020, split by share class structure. The presented statistics are computed after winsorizing the variables. Columns (1) to (4) and (5) to (8) reports the number of observations, mean, median and standard deviation of the sub-samples single-class firms and dual-class firms. All variables are winsorized at 1% and 99% level.

	Obs	Mean	Median	S.D.
	(1)	(2)	(3)	(4)
Dependent variables				
Patentcount	2,441	6.98	0.00	29.10
Patentcount/R&D	1,276	0.05	0.00	0.19
R&DIntensity (%)	2,441	4.03	0.07	8.51
Control variables				
ROA (%)	2,441	4.33	7.01	16.22
LnSales	2,441	7.34	7.31	2.24
Tobins Q	2,428	4.00	2.45	5.76
Leverage (%)	2,441	18.96	17.32	15.75
CAPEXIntensity (%)	2,336	2.46	1.54	2.68

Table 13

Correlation matrix 2

The table reports the correlation coefficient between all variables employed in our full model specifications. The statistics were computed after winsorizing the variables, for 1,240 observations in our sample. 1,201 observations are not accounted for in the correlation matrix due to missing observations in *Patencount/R&D* and *CAPEXIntensity*.

		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
DCS	(1)	1.00								
Patentcount	(2)	0.23	1.00							
Patentcount/R&D	(3)	0.06	0.05	1.00						
R&DIntensity	(4)	-0.17	-0.06	-0.09	1.00					
ROA	(5)	0.11	0.08	-0.10	-0.57	1.00				
LnSales	(6)	0.30	0.48	-0.12	-0.50	0.52	1.00			
TobinsQ	(7)	-0.07	-0.07	-0.01	0.31	-0.09	-0.20	1.00		
Leverage	(8)	0.04	0.11	-0.09	-0.33	0.10	0.39	-0.02	1.00	
CAPEXIntensity	(9)	0.05	0.11	0.03	-0.16	0.11	0.25	-0.03	0.13	1.00

Table 14

High-technology Industries and six-digit GICS Codes

This table reports the industry names and corresponding six-digit GICS Code combinations for our subsample of high-technology firms.

Industry Name	GICS Code
Electrical Equipment	201040
Internet and Catalog Retail	255020
Health Care Equipment and Supplies	351010
Health Care Technology	351030
Biotechnology	352010
Pharmaceuticals	352020
Life Sciences Tools and Services	352030
Internet & Software Services	451010
Information Technology Services	451020
Software	451030
Communications Equipment	452010
Computers and Peripherals	452020
Electronic Equipment and Instruments	452030
Semiconductor Equipment	452050
Semiconductors	453010
Diversified Telecommunications Services	501010
Wireless Telecommunications Services	501020

Table 15

Definition of variables

This table reports the definition of variables used in the regressions. The variables have been calculated on the firm level per annum. All variables have been winzorized at the 1% and 99% level.

	Description
Main variables	
DCS	Dummy variable indicating whether a company has dual-class share structure
Patentcount	Number of patents
Patentcount/R&D	Number of patents divided by R&D expenditure
R&DIntensity	R&D expenditure divided by total assets year end
Control variables	
LnSales	Natural logarithm of revenue
ROA	Earnings before interest and taxes divided by total assets
Leverage	Total debt divided by total assets
TobinsQ	Market value of equity divided by book value of equity
CAPEXIntensity	Capital expenditure divided by total assets