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The Fundamental Drivers of Merger Waves

A study of industry level merger activity in the Nordic market

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Abstract

We examine if merger waves occur on an industry level in the Nordics, and the underlying drivers of these waves. We conduct simulations of the empirical distribution of merger activity, univariate tests and regressions of logit models to address this research question. Further, we propose the use of an index, based on principal component analysis of key operating performance measures, to capture economic shocks. Our findings suggest the existence of a complex relationship between merger waves and economic shocks, capital liquidity constraints and stock market booms. In conclusion, we find evidence for the neoclassical theory of merger waves, indicating economic shocks are the fundamental drivers of merger waves on an industry level in the Nordics. Using the implications from our study, firms can reposition themselves in anticipation of demand shocks to take full advantage of periods with intense merger activity.

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1. Introduction

The purpose of our thesis is to examine merger waves on an industry level and to identify the fundamental drivers behind them. This quantitative study is of particular interest to investors and managers engaging in mergers and acquisitions (M&A) and contributes to the theoretical framework by exploring the phenomenon in a new context. We study the Nordic market in pursuit of answering the following research question:

Do merger waves occur on an industry level in the Nordics, and what are the underlying drivers of these waves?

M&A has long been of considerable interest for numerous actors in the global economy and is among the most visible expression of corporate strategy. It is common practice amongst companies to engage in M&A to stimulate growth, gain competitive advantages and increase market shares (Schweizer, 2005). Due to the complex nature of M&A, researchers have tended to consider only partial explanations, resulting in an incomplete understanding of the topic (Larsson and Finkelstein, 1999). A frequently studied phenomenon is that M&A activity clusters in time to create merger waves. Even though the notion of mergers occurring in waves is virtually undisputed, there is no clear consensus on defining a merger wave in a time series context (Gärtner and Halbheer, 2009). While much research exists on the motives and consequences of mergers, surprisingly little exists on the causes of merger waves (Gugler et al., 2012). Primarily studied in the US, the 1990's wave caught the attention of researchers on a global scale. For the first time, M&A activity in Europe hit the levels of the US. Various technological, economic, and industry shocks, such as introducing the Euro, globalisation, technological innovations, and a financial market boom spurred European merger activity (Martynova and Renneboog, 2008).

Previous literature has identified and studied six distinct aggregate merger waves during the last century (Martynova and Renneboog, 2008; Berk and DeMarzo, 2016). Furthermore, studies have identified these occurrences on an industry level (Mitchell and Mulherin, 1996; Harford, 2005). Empirically, two competing theories exist: neoclassical and behavioural. The neoclassical theory rationally explains merger waves. The industry shock theory is essential in the framework and states that waves are consequences of economic, technologic, or regulatory disturbances, i.e. shocks that alter industries operating environment (Gort, 1969). The shocks can impact industries either positive or negative, sparking M&A activity (Mitchell and Mulherin, 1996). Harford (2005) argues aggregate merger waves are a cause of industries experiencing shocks simultaneously in times of high capital liquidity. He summarises his results as:

> *"[...] the explanation for merger waves is intuitive: they require both an economic motivation for transactions and relatively low transaction costs to generate the large volume of transactions"*

In contrast to the neoclassical theory, the behavioural theory provides an irrational explanation for merger waves. The overvaluation and managerial discretion theory, both categorised as behavioural, assume inefficient capital markets. Schleifer and Vishny (2003) propose a model based on the overvaluation theory, built on the empirical evidence from historic merger waves. According to their research, managers take advantage of stock market inefficiencies through merger decisions. Merger activity will cluster in time and create merger waves when industry valuations are high and firm overvaluation is common. Rhodes-Kropf and Viswanathan (2004) contribute by developing a model for merger waves based on the misperceived merger synergies. These misperceptions allow rational target managers to accept overvalued equity as a transaction medium during stock market booms. The managerial discretion theory predicts that managers engage in empire building during periods of high market optimism, leading to an overrepresentation of wealth-destroying mergers during waves.

The literature regarding merger waves is scarce, and since multiple definitions of merger waves exists explanations vary. Contradicting result in previous literature could be a cause of methodological reasons or due to different markets or periods studied. To the best of our knowledge, no previous study has examined the fundamental drivers of merger waves in the Nordics. We aim to address this gap by studying the Nordic M&A market and contribute to an improved understanding of this phenomenon in a new context.

Our findings suggest merger waves are common but driven by a complex relationship between economic shocks, capital liquidity constraints and stock market booms. When capital liquidity is abundant, industry shocks create an environment where the reallocation of assets through M&A is favourable. The industry-level merger waves seem to cluster in time, implying simultaneous industry shocks cause aggregated waves. Our study differs from previous literature when predicting the occurrence of merger waves. We propose an index, capturing economic shocks, by adapting the procedure brought forward by Nardo et al. (2008). Our results contribute to the prevailing literature by adding empirical evidence from the Nordic market to the frameworks used to examine M&A activity.

The study covers M&A bids made by Nordic companies between 2000-2019. We include observations from 1996-1999 for lagged variables in the models. Due to the inclusion of stock-based data, we limit ourselves to M&A bids made by publicly listed firms. Furthermore, we use M&A bids above $10M where an acquirer sought to acquire more than 50% of the target. Even though Iceland is a part of the Nordics, we exclude these observations since the Icelandic economy was severely affected by the financial crises and could distort our results (Legutko, 2017). We deem analysis of acquirers' stock returns following merger waves outside the study's scope, as analysing the industry characteristics prior to a wave should provide sufficient indications towards the fundamental drivers of a merger wave. Since theories within each category make similar predictions, we have decided to limit the study to the two wider groups: neoclassical and behavioural.

The study consists of six sections. Section 2 contains a review of previous literature and theories followed by the development of the hypotheses. Section 3 explains the method used to identify mergers waves, the construction of the index used as a proxy for economic shocks, and the test and models used to identify the underlying drivers of merger waves. Section 4 presents descriptive statistics, the results and analysis of the tests and regressions. In section 5, we discuss the results and our proxy for economic shocks. Section 6 concludes.

2. Literature Review

This section provides an overview of prior merger wave research, including the two competing theories used to explain the phenomenon: the neoclassical and the behavioural theory. Lastly, we present the development of our hypotheses.

2.1 Merger waves

A widely accepted conjecture in the economic literature is that the level of merger activity clusters in time (Golbe and White, 1993). Stigler (1950) was among the first to observe the cyclical pattern of M&A activity. Stigler (1950) stipulates that the first merger wave in the

1890’s, also named the Great Merger Wave, resulted from fundamental changes in technology, economic expansion, and innovation in industrial processes. Previous literature has additionally identified five other distinct aggregate merger waves. These waves occurred in the 1920’s, the 1960’s, the 1980’s, the 1990’s and the 2000’s (Martynova and Renneboog, 2008; Berk and DeMarzo, 2017).

All studies are unanimous as to what constitutes the core of a merger wave, clustering of merger activity. However, previous literature applies various methods and definitions when identifying merger waves. For instance, Golbe and White (1993) identify waves by fitting a sine curve to historical merger data, whilst others such as Mitchell and Mulherin (1996) define it as a cluster of M&A bids within a particular industry over a 24-month period. Harford (2005) extends this definition, stating that there could only be one merger wave per industry and decade. He employs a method of comparing empirical distributions of merger activity to actual merger data. It is possible to account for different industry structures by distinguishing between merger waves on an aggregated and industry-specific level (Mitchell and Mulherin, 1996; Harford, 2005). Factors such as economic shocks and stock market returns could have different effects across firms and industries. Hsu et al. (2017) study the underlying motives on M&A activities in the upstream oil & gas (O&G) sector in the US and conclude that there are industry-specific factors driving merger waves in the O&G industry. While factors related to the stock market can drive aggregated merger waves, the O&G industry is sensitive to oil and gas production and prices.

Previous studies indicate that merger waves can have impressing magnitudes with substantial differences between wave and non-wave activity. By analysing US acquisitions with a transaction value of at least $50 million between 1981 and 2000, Harford (2005) identifies 35 waves within 28 industries. The average number of bids in a non-wave period was 7.8 and 34.3 in-wave. Furthermore, he finds clear links between aggregated and industry-specific merger waves and concludes that simultaneous industry shocks cause aggregated merger waves. However, the investigation of industry level merger activity by Gärtner and Halbheer (2009) does not support the findings of Mitchell and Mulherin (1996) and Harford (2005). Their study reveals that there is no sign of clustered merger activity within multiple industries that creates aggregate merger waves. Consequently, there is no clear evidence on industry-specific merger waves or any consensus as to why they occur. Previous literature broadly categorises the competing explanations into two groups: neoclassical and behavioural.

2.2 The Neoclassical theory of merger waves

The neoclassical theory consists of the industry shock theory and the q-theory of mergers. The theory explains merger waves with rational assumptions such as efficient capital markets. Empirical studies of different merger waves have found evidence suggesting that shocks lead to clustering of merger activity (Mitchell and Mulherin, 1996; Harford, 2005). A shock alters industry structure, characteristics, and firms' operating environment, not seldom caused by significant events such as deregulation, input price volatility, demographic, or technological change. Economic disturbances lead to industry reorganisation, creating environments where mergers are an efficient approach to acquire assets (Gort, 1969). The shock disturbs the industry sector and can affect it either positively or negatively. Mitchell and Mulherin (1996) analyse the 1980's merger wave. On average, half of the takeovers and restructurings in any industry took place in one-fourth of the sample period. Both sales and employment shocks, estimated from surviving firms during the 1980's, were positively and significantly correlated to M&A activity on an industry level. The relation between industry shocks and takeover activity was not merely driven by firm-specific factors, reflecting an industry-wide phenomenon. Hence, there must be a collective reaction of firms inside and outside the industry once a technological, regulatory, or economic shock occurs to acquire assets through M&A, resulting in clusters of merger activity.

Harford (2005) presents evidence for the neoclassical theory being the driver of industry-specific merger waves. In addition to industry shocks, he argues that high capital liquidity is an integral component to explain merger waves. High market valuations relax financing constraints, making market valuation essential in estimating capital liquidity. This reasoning is also mentioned by Stigler (1950) when describing the drivers behind the 1920s merger wave. The degree of capital liquidity is cyclical, and variations in the liquidity impact total capital reallocation in the economy (Eisfeldt and Rampini, 2006). Empirical evidence brought forward by Harford (1999) shows that the probability of being a bidder increases with cash-richness and that firms with built-up cash reserves are more active in the acquisition market. These results indicate a linkage between capital liquidity and M&A activity.

Major deregulatory events cause changes to industries' structure and operating environment (Mitchell and Mulherin, 1996). According to empirical studies, shocks resulting from deregulation was one of the primary drivers of the 1990's merger wave in the US (Andrade et al., 2001; Harford, 2005). The studies assume deregulations are unexpected and exogenous, meaning they lack predictability. However, in a recent empirical study Ovtchinnikov (2013) challenges this view. He analyses the mergers waves caused by deregulatory events and argues that these shocks are endogenous. He finds that deregulation is preceded by poor industry performance, being predictable using various performance measures. Before deregulations, industries tend to have low profitability and solvency, combined with high leverage and capital expenditures.

According to the q-theory, increased dispersion of q-ratios results in amplified merger activity (Jovanovic and Rousseau, 2002). A firm's q-ratio equals the ratio between a firm's market capitalisation and its replacement cost of capital, estimating overvaluation or undervaluation (Tobin and Brainard, 1976). The source of the increased dispersion is accredited to underlying technological shocks, causing stock prices and consequently q-ratios to rise, leading to profitable mergers and thereby generating merger waves (Jovanovic and Rousseau, 2002). Andrade et al. (2001) find an overrepresentation of acquirers with higher q-ratios. Concurrently, lower q-firms were more likely to be acquired. The q-theory provides an extension to the industry shock theory. However, a significant difference is that the industry shock theory assumes the existence of numerous shocks, such as coinciding technological, economic, and regulatory shocks.

The q-theory and the industry shock theory differ regarding what constitutes a disruptive shock. Nevertheless, the effect experienced by firms within an industry should be observable through key fundamental performance measures. Therefore, by examining operating performance measures, one may either reject or confirm the neoclassical hypothesis of merger waves.

2.3 The Behavioural theory of merger waves

The behavioural theory primarily consists of the overvaluation theory and managerial discretion theory. In contrast to the neoclassical theory, the behavioural theory allows for irrationality. The assumption of perfect capital markets is relaxed, and managers can make decisions based on self-interest. Shleifer and Vishny (2003) argue that clustering in merger activity is caused by stock market valuations of merging firms and the markets misperception of merger synergies. The fundamental assumption, in theory, is that financial markets are inefficient. During stock market booms, firms become overvalued and managers’ constraints are relaxed. Acquiring managers are rational and take advantage of stock market inefficiencies through merger decisions by trading overvalued equity for assets. Hence, when valuations are high, the frequency of stock mergers should increase whilst cash mergers should be overrepresented when valuations are low. The target managers do not maximise long-term shareholder value but instead try to maximise their short-term gains given the current market or firm-specific misvaluations. However, the asymmetric information could cause merger waves even with rational target managers due to the misperception of merger synergies (Rhodes-Kropf and Viswanathan, 2004).

Misvaluation has two components, firm-specific and market-wide. Uncertainty of the source of misvaluation will lead to a correlation between overall market performance and merger activity. Thus, potential valuation errors made by acquirer and target managers rationally induce merger waves. Misvaluation of the potential synergies in times of overvaluation will lead to target managers accepting lower bids and overvalued equity, partly explained by the imperfect information they possess. The models proposed by Schleifer and Vishny (2003) and Rhodes-Kropf and Viswanathan (2004) make similar predictions but differ in the rationality of target managers. Regardless, prevailing literature group both theories as behavioural due to their dependence on acquiring managers taking advantage of market inefficiencies and firm-specific misvaluations. Their models further propose that aggregate merger activity will be higher in an overvalued stock market, creating aggregate merger waves. Rhodes–Kropf et al. (2005) find that large dispersions in market-to-book ratios are positively correlated with merger intensity. Further, their results show that low value-to-book firms buy high value-to-book firms due to dispersions in firm-specific errors in valuation.

The managerial discretion theory assumes that managers benefit from growing their firm, either due to empire building or because they have personal income tied to firm growth. As stock market valuations increase, so does market optimism. During periods of market optimism, managers can engage in wealth-destroying mergers without the risk of reprimands through share price falls. The theory states that firms which are not overvalued may still engage in M&A activity if cash is in abundance. Market optimism creates an environment where shareholders expect these mergers to generate synergies, even when they are non-existent. Further, one should expect the number of wealth-destroying mergers to be inversely related to the fraction of shares held by the largest shareholder (Gugler et al., 2012). Further, Gugler et al. (2012) analyse the determinants of merger waves in the US, UK, and Continental Europe during 1991-2004 for both listed and unlisted firms. By employing a model to predict high states of merger activity, they analyse the differences between the two types of companies. For the US, UK and Continental Europe, periods with apparent clustering of merger activity is exclusive to listed firms. The observed patterns are consistent with the predictions of the behavioural theory of merger waves. Furthermore, optimism associated with stock market booms explains both the increase in merger activity during booms and the subsequent adverse effects of the mergers on shareholder return for listed companies.

In contrast to the managerial discretion theory, the overvaluation theory does not include the principal-agent problem faced by acquiring shareholders (Gugler et al., 2012). Hence, the overvaluation theory predicts that the merger activity of listed companies is positively correlated with the fraction of shares held by the largest shareholder. The overvaluation theory states that the amount of stock mergers should increase in merger waves, whilst the managerial discretion theory makes no prediction regarding changes in the transaction medium. Even though the theories differ in these regards, both expect merger waves to correlate with share price performance and overvaluation.

2.4 Major differences between the neoclassical and behavioural theories

The q-theory of mergers predicts that high-q firms will acquire more assets than low-q firms. The explanatory power solely relies on the dispersions in q-ratio. Rhodes-Kropf et al. (2005) find that dispersions in valuation is positively correlated with merger intensity, but firms with low valuation buy firms with high valuation, the opposite of the prediction made by the q-theory. Further, the manager discretion theory states that stock returns are significant in explaining merger activity, even when considering the q-ratio of acquirers. The reasoning for this discrepancy is that the latter captures the effect of market optimism. The behavioural cannot explain mergers financed by debt or cash, stating the use of shares, or cash received by issuing new equity, as the transaction medium during a merger wave should increase. In contrast, the financing component in the industry shock theory holds when borrowing costs are low, creating an environment of low capital constraints. Since the theory assumes efficient capital markets, equity financing should not be more beneficial than using debt or cash. Consequently, the fraction of stock mergers should not increase during a merger wave.

The industry shock theory implies that merger waves occur as firms react to radical changes in their operating environment. Overall valuation or other stock-based metrics should not systematically coincide with merger waves, unless induced by shocks. Managers should therefore be under equal constraints, regardless of valuation or stock performance. These assumptions are relaxed under the overvaluation theory and the managerial discretion theory, allowing for exploitation of inefficient capital markets. One conundrum arising when comparing the neoclassical and behavioural theory is that significant advances in an industry resulting from a shock often correlate with stock market booms. If the neoclassical theory holds, the merger waves should correlate with proxies used to identify shocks, regardless of the stock market reaction.

2.5 Hypotheses development

Based on the abovementioned theoretical framework, our hypotheses are derived. Three main underlying arguments are motivating our three hypotheses:

(1) Mergers are clustered in time, both on an aggregated and an industry level. Even though evidence from the Nordics is limited, it is reasonable to believe that M&A activity in the Nordics should follow the same pattern found in the US, UK, and Continental Europe given the global nature of the modern economy.

(2) Researchers have found empirical evidence supporting the neoclassical theory of mergers. Merger waves occur when industries react to a shock in their operating environment. If the neoclassical hypothesis holds, there should be observable technology, economic and/or regulatory shocks preceding the wave. Given the capital liquidity component, merger waves will coincide with low capital constraints in the market.

(3) The behavioural theory states that the underlying driver of mergers is overvaluation in the market and that managers use overvalued stock to reallocate capital. Consequently, two predictions emerge. (i) Merger waves will occur following periods of abnormally high stock returns or market-to-book ratios. (ii) Technology, economic and/or regulatory shocks will not systematically precede the wave.

In conclusion, we expect Nordic M&A activity to cluster in time, creating merger waves. Regarding drivers of merger waves, current evidence is contradicting. The majority of previous studies point towards the neoclassical or behavioural theory as the principal explanations. However, they seldom entirely reject the opposing explanation. Therefore, we anticipate the neoclassical or the behavioural theory to explain merger waves in the Nordics. Formally stated, our three hypotheses are:

H1: Merger activity in the Nordic is characterized by merger waves.

H2: There is a positive association between merger waves and industry shocks.

H3: There is a positive association between merger waves and overvaluation.

3. Methodology

This section provides a detailed description of our methodology used to identify and analyse merger waves. Moreover, our models are presented, together with the dependent and independent variables. Lastly, we present our samples and sample construction processes.

3.1 Process of identifying Merger waves

The data is divided into two subsets, 2000-2009 and 2010-2019, as two different market conditions characterised them. The 2000's experienced high volatility induced by the peak and recession following the IT-bubble and the financial crisis of 2008. However, the 2010's was a 10-year recovery period, only interrupted by short periods of bear markets because of geopolitical conditions (Petterson et al., 2019). Dividing the sample into two subsamples due to difference in market conditions is in accordance with the definition used by Harford (2005).

We limit the length of a merger wave to 24-months and follow the simulated approach used by Harford (2005) to identify these waves with a statistically significant method (Mitchell and Mulherin, 1996). We assign acquirers and targets into 48 different industry groups classified by Fama and French (1997) based on each acquirer's or target's SIC-code as recorded at the time of the merger. Firms may have deviated from their original industry group during the sample period, and the use of historical SIC-codes captures this effect. For each industry and decade, we calculate the highest concentration of merger bids. The first month of the 24-month period with the highest concentration of merger activity, the peak, is recognised as the start of a potential merger wave. Since we study merger activity in each industry group, diversifying mergers will be counted towards both the acquirer and target industry. We define a diversifying merger as an acquirer and target from two separate industry groups. If the acquirer and the target are in the same industry, the bid only counts towards that industry once (Harford 2005).

The first step in distinguishing actual merger waves from potential merger waves is to simulate the empirical distribution of the actual number of merger bids in each industry. Using Python code, we randomly assign each merger a number between 1-120, one for each month in a decade, with an equal probability of 1/120. Next, we extract the 24-month period with the highest concentration of merger bids. We perform the simulation a total of 10 000 times per industry-decade. Finally, we compare the highest concentration of merger bids in each simulation to the actual number of merger bids in the peak. If the actual number of merger bids in the peak exceeds the 95th percentile from the peaks of all the empirical distributions, we classify the 24-month period as a merger wave (Harford 2005).

3.2 Univariate test

We employ a univariate test, in form of an one sample t-test, to examine the sets of factors predicted by the neoclassical and behavioural theories. We investigate if the proxies used for industry shocks, overvaluation and market optimism are significantly above their mean during pre-wave years. We use pre-wave years to investigate if changes in the predictors correlates the start of merger waves.

For all variables, we calculate the industry-year median and rank the observations into quartiles based on each industry and variable. All industry-years within the sample are therefore assigned a number between one and four for each variable. Since our data set consists of a 20-year time series, the intra-industry middle rank for each variable is 2.5. We perform a t-test to examine if the cross-industry mean rank of the variables in the pre-wave year is significantly above the time-series middle rank of 2.5, which is the null hypothesis. *Mean rank* is the observed mean rank in the sample, *SD(mean rank)* is the standard deviation of the mean rank, and *n* is the total number of observations. We then apply the following formula and conduct a t-test.

$$t = \frac{mean\,rank - 2.5}{SD(mean\,rank) \times \frac{1}{\sqrt{n}}}$$

A key prediction made by the behavioural theory is that the fraction of stock mergers should increase during merger waves. To test this prediction we employ a t-test on the difference between the cross-industry frequency of stock mergers in a merger wave and its time-series mean. *FSM* is the frequency of stock mergers as a percentage of total mergers in each industry-year and $\overline{FSM}$ is the mean frequency of stock mergers during the sample period. *SD(FSM)* is the standard deviation of the frequency, and *n* is the total number of observations. The t-test for stock merger frequency takes on the following formula:

$$t = \frac{FSM - \overline{FSM}}{SD(FSM) \times \frac{1}{\sqrt{n}}}$$

3.2.1 Proxies used to measure industry shocks

According to Ovtchinnikov (2013), deregulation is an endogenous shock predictable with operating performance measures. Therefore, we exclude deregulation as a stand-alone variable in the analysis. Technology and economic shocks could have different directional effects across firms and industries. Therefore, we calculate the absolute change of each variable, which is in accordance with Harford (2005). To produce a proxy for economic shocks, we use key fundamentals data for all listed firms in the Nordics during the sample period. We present the variables below.

SG – We define sales growth (*SG)* as the absolute change of the natural logarithm of total revenue in year t divided by total revenue in year t-1. We expect positive shocks to positively correlate with the aggregate sales growth in an industry. Others define sales growth as the percentage change; however, using the natural logarithm of the expression, the negative and positive growth has the same absolute value. We use two-year sales growth (*2yr-SG)* to capture the lagging effects of industry shocks on merger waves. The use of sales growth as a proxy for industry shocks is in accordance with Mitchell and Mullherin (1996) and Harford (2005).

$$SG_t = abs\left(\ln\left(\frac{Sales_t}{Sales_{t-1}}\right) - \ln\left(\frac{Sales_{t-1}}{Sales_{t-2}}\right)\right)$$

$$2yr - SG_t = abs\left(\ln\left(\frac{Sales_t}{Sales_{t-2}}\right) - \ln\left(\frac{Sales_{t-1}}{Sales_{t-3}}\right)\right)$$

EG – We define employee growth (*EG)* as the absolute change of the natural logarithm of the number of employees in year t divided by the number of employees in year t-1. We use the natural logarithm based on the same reasoning used when calculating *SG*. The selection of this variable is motivated by previous research made by Mitchell and Mulherin (1996) to measure industry shocks and firm performance by Healy et al. (1992).

$$EG_t = abs\left(\ln\left(\frac{Employees_t}{Employees_{t-1}}\right) - \ln\left(\frac{Employees_{t-1}}{Employees_{t-2}}\right)\right)$$

NIM – To measure bottom-line profitability in each industry, we use the absolute change of net income over sales (*NIM*) (Harford, 2005).

$$NIM_t = abs\left(\frac{Net\ Income_t}{Sales_t} - \frac{Net\ Income_{t-1}}{Sales_{t-1}}\right)$$

ROA – We define return on assets (*ROA)* as the absolute change of EBIT in year t divided by the book value of total assets at the end of year t-1. According to Thanos and Papadakis (2012), it is the most widely used and accepted operating performance measure in M&A literature. We use both *ROA* and *NIM* to capture industry shock effects on profitability (Harford, 2005).

$$ROA_t = abs\left(\frac{EBIT_t}{Total\ Assets_{t-1}} - \frac{EBIT_{t-1}}{Total\ Assets_{t-2}}\right)$$

AT – We calculate asset turnover (*AT*) as the absolute change of sales in year t over assets reported in the balance sheet in year t-1. This operating performance ratio measures the sales in relation to investments in assets and indicates how efficient firms generate sales from their employed assets. Using asset turnover in the analysis of economic shocks is motivated by Healy et al. (1992).

$$AT_t = abs\left(\frac{Sales_t}{Total\ Assets_{t-1}} - \frac{Sales_{t-1}}{Total\ Assets_{t-2}}\right)$$

CAPEX – We define *CAPEX* as the absolute change of capital expenditures divided by the book value net property plant and equipment (Net PPE). We use this variable to measure capital intensity within an industry. Shifts in industry structure should affect the capital intensity positively or negatively depending on the direction of the shock and the prospectus of the firms (Healy et al., 1992; Harford, 2005).

$$CAPEX_t = abs\left(\frac{Capital\ Expenditures_t}{Net\ PPE_t} - \frac{Capital\ Expenditures_{t-1}}{Net\ PPE_{t-1}}\right)$$

R&D – The final variable used to proxy industry shocks is *R&D*, defined as the absolute change of research and development expenses over the book value of intangible assets. The reasoning is analogous to the usage of *CAPEX*, where we measure R&D intensity (Healy et al., 1992; Harford, 2005).

$$R\&D_t = abs\left(\frac{R\&D\ Expenses_t}{Total\ Intangible\ Assets_t} - \frac{R\&D\ Expenses_{t-1}}{Total\ Intangible\ Assets_{t-1}}\right)$$

3.2.2 Proxies used to measure overvaluation and market optimism

To closer examine if managers exploitation of firm overvaluation and market inefficiencies when acquiring target companies lead to clustering of merger activity, we apply a univariate analysis based on the following variables: *1yr-Return* and *3yr-Return*, combined with the standard deviation of those variables on an industry level (Harford, 2005). Further, we include *2yr-Return* and the intra-industry dispersion of that return. All returns are dividend-adjusted. We expect high returns and dispersion in the returns to coincide with merger waves.

The market-to-book ratio (*MB*), defined as the market capitalisation divided by the book value of equity, proxies for overvaluation and is used in similar research by Rhodes-Kropf et al. (2005). However, we note that Harford (2005) also uses *MB* as an indicator for capital liquidity constraints since he assumes an inverse relationship between the two. We exclude firm-year observations with negative equity.

$$MB_t = \frac{Market\ Capitalization_t}{Book\ Value\ of\ Equity_t}$$

We use the intra-industry standard deviation of *MB* to proxy for dispersions in valuation as we expect it to positively correlate with increased merger activity (Rhodes-Kropf et al., 2005).

$$\sigma(MB)_t = \sum_{i=0}^{n} \frac{MB_t - \overline{MB_t}}{n-1}$$

We include the change in *MB* to measure significant changes in valuation (Harford, 2005).

$$\Delta\, MB_t = MB_t - MB_{t-1}$$

3.3 Multivariable tests and prediction of merger waves

In this section, we present the methodology for comparing the complete sets of variables related to the different hypotheses and seek to predict merger waves. To accomplish this, we use four different logit regression models.

3.3.1 Principal component analysis

All firm-specific variables are proxies for industry shocks. To reduce amount of shock proxies, we perform a principal component analysis (PCA). PCA is a multivariate technique for dimension reduction of a dataset. It is applied to reduce the number of variables whilst still maintaining high explanatory power. PCA reduces a large set of independent variables to an uncorrelated set, called principal components. PCA is sensitive regarding the variance of the initial variables, implying the variables with the highest variance will dominate. Therefore, the initial variables are standardised, with a mean of 0 and a standard deviation of 1.

The first principal component is the best fitting line between the observations in the dataset, which is the line that minimises the average squared standard error. The second principal component is the second-best fitting line and is perpendicular and uncorrelated to the first. This process continues until there are as many principal components as variables. Principal components account for different amounts of the total variance in the original variables in descending order. Using the results from the PCA, we reduce the eight shock variables into one variable, named the Economic Shock Index (*ESI*).

3.3.2 Construction of the Economic Shock Index

We derive the *ESI* using the procedure proposed by Nardo et al. (2008) when constructing indices from PCAs. We base the index on the economic shock variables related to the neoclassical hypothesis. The first step is to predict the principal components and extract their respective eigenvalues, which explain the significance of a principal component. Components with eigenvalues above one are significant; therefore, we exclude the components with eigenvalues below one from the index. We perform an orthogonal varimax rotation to minimise the number of variables with high loadings on more than one principal component. Component loadings, interpreted as the correlation of each item with the principal component, and a loading above 0.3 is considered high. The second step is to reduce the data dimensions and obtain a single index measure that proxies for economic shocks. We construct the index by multiplying the value of the principal components for each industry-year with their respective proportion of the total explained variance.

Three principal components have eigenvalues above one and included in the calculation of the *ESI*. The variables *SG*, *2yr-SG*, *EG* and *AT* load significantly on the first principal component, while *NIM*, *ROA* and *CAPEX* load significantly on the second principal component. *R&D* loads significantly on the third principal component. The three principal components explain 61.2% of the total variance. The weight for the first component (*w1*) is calculated as 0.284/0.612, the second (*w2*) 0.195/0.612 and the third (*w3*) 0.134/0.612. The index takes on the following formula:

$$ESI = 0.464 * Component\ 1 + 0.319 * Component\ 2 + 0.219 * Component\ 3$$

Table 1a: PCA – Principal components derived

	Eigenvalue	Proportion	Cumulative
Component 1	2.271	0.284	0.284
Component 2	1.558	0.195	0.479
Component 3	1.069	0.134	0.612

Table 1b: PCA – Variables loadings on components

Variable	Component 1	Component 2	Component 3
SG	0.489	0.091	-0.099
2yr-SG	0.496	0.073	-0.110
EG	0.435	-0.147	-0.198
NIM	-0.080	0.653	-0.198
ROA	0.291	0.405	0.217
AT	0.484	-0.188	0.262
CAPEX	0.014	0.582	0.158
R&D	-0.021	-0.015	0.871

To account for the capital liquidity argument advanced by Harford (2005) we include a macro component which proxies for capital liquidity. The proxy used is the rate spread (*RS)* between the average Swedish commercial lending rate non-financial companies, and the Swedish central marginal rate. While commercial and industrial credit availability does not have a proven causal effect on merger waves, the rate spread may be a proxy for overall liquidity (Lown et al., 2000; Harford 2005). Swedish firms constitute a considerable portion of our sample, and Sweden is the largest economy of the four countries. Therefore, the Swedish rate spread functions as a proxy for the overall rate spread in the Nordic countries. We continue by deriving the dummy variable Tight Capital (*TC*) that interacts with the index in the regression model. *TC* is equal to 1 for all low capital liquidity industry-years. We define low capital liquidity years as industry-years when market-to-book ratios are below their industry-specific time-series median or *RS* is above its time-series median.

3.3.3 Logit models

We utilise logit models to determine if the neoclassical or the behavioural theories best describe the drivers behind merger waves. The logit model excludes assumptions concerning distribution, linearity, and homoscedasticity due to its non-linear nature. However, the logit model makes several assumptions regarding the observations and the variables (Christensen, 1990). Firstly, it must be a random sample of observations. The dependent variable Y is a binary variable and is caused by or associated with the independent variables. The independent variables should not show signs of high correlation or multicollinearity. Finally, there is uncertainty in the relationship between the dependent and independent variables. We allow for correlation between industry-year by clustering the standard errors by industry (Nardo et al., 2008). We present the four logit regression models in detail below and the predicted signs of their coefficients in Table 2.

In all regressions, L denotes that they are logit function. *Wave Start* is a dependent dummy variable that takes on the value 1 if the industry-year is the start of a merger wave, and we measure all independent and control variables at the end of year t-1. The first logit model consists of *MB* since both theories claim it. The formula for the first regression takes on the following form:

$$P(Wave\ Start_t \mid x) = L(\beta_0 + \beta_1 MB_{t-1})$$

We base the second model on the variables related to the behavioural hypothesis and add *σ(MB), 1y-Return* and *σ(1yr-Return*). The regression indicates whether the behavioural theory explains the underlying drivers of merger waves in the Nordic market. The regression takes on the following formula:

$$P(Wave\ Start_t \mid x) = L(\beta_0 + \beta_1 MB_{t-1} + \beta_2 \sigma(MB_{t-1}) + \beta_3 1yr - Return_{t-1} + \beta_4 \sigma(1yr - Return)_{t-1})$$

The third logit regression model examines if all the variables related to the neoclassical theory could predict merger waves. We test *ESI* controlling for RS*, ESI×TC,* and *TC*. *RS* accounts for the overall capital liquidity in the market. *ESI×TC* captures the prediction that capital liquidity is needed for an industry shock to generate a merger wave. The third regression takes on the following form:

$$P(Wave\ Start_t \mid x) = L(\beta_0 + \beta_1 ESI_{t-1} + \beta_2 RS_{t-1} + \beta_3 TC_{t-1} + \beta_4 (ESI \times TC)_{t-1})$$

Lastly, in the fourth combined logit model in which all variables, both those related to the behavioural and neoclassical, are tested simultaneously to see if they as a group could predict merger waves in the Nordic M&A market. The combined model is the following:

$$P(Wave\ Start_t \mid x) = L(\beta_0 + \beta_1 MB_{t-1} + \beta_2 \sigma(MB_{t-1}) + \beta_3 1yr - Return_{t-1} + \beta_4 \sigma(1yr - Return)_{t-1} + \beta_5 ESI_{t-1} + \beta_6 RS_{t-1} + \beta_7 TC_{t-1} + \beta_8 (ESI \times TC)_{t-1})$$

Table 2: Predicted signs of coefficients

Variables	Neoclassical		Behavioural	
	Expected sign	Proxies for	Expected sign	Proxies for
MB	+	Capital liquidity contraints	+	Overvaluation
σ (MB)	+	Dispersions in q-ratios	+	Dispersions in valuation
1yr-Return	?	Makes no prediction	+	Market optimism and stock market boom
σ (1yr-Return)	?	Makes no prediction	+	Dispersion in short-run returns
ESI	+	Economic shocks	?	Makes no prediction
RS	+	Overall capital liquidity	?	Makes no prediction
TC	-	Low capital liquidity years	?	Makes no prediction
ESI × TC	-	Economic shocks during periods of low capital liquidity	?	Makes no prediction

Notes: The table shows the predicted signs of the coefficients in the logit models. Additionally, we state what the variables proxy for in each theory.

3.4 Sample

3.4.1 Data collection process

We use three different datasets: (1) M&A bids in the Nordic market during 2000-2019, (2) historical financial data on all publicly listed Nordic companies during the relevant period, and finally (3) stock returns and market capitalisation for all listed Nordic companies. We retrieve the M&A data in the first dataset from the SDC Platinum database at the Swedish House of Finance. The second dataset is retrieved from the WRDS Compustat database by country and later merged into one complete dataset. Lastly, we source the third dataset from Capital IQ. All datasets also contain Historical Standard Industrial Classification (SIC) codes to cross-reference the Fama and French (1997) industry classification between datasets.

3.4.2 Sample construction

We include all bids equal to and above $10M to retrieve a sufficient sample of M&A bids and exclude smaller bids due to their potentially low explanatory power. Previous research, primarily from the US market, excludes mergers with a deal value below $50M (Harford, 2005). However, since the Nordic market is smaller than the US market, the sample size in the study will significantly decrease if we use $50M.

We exclude financial industry groups, such as *Banking*, *Insurance*, *Trading* and *Real Estate*, from the final sample. Firstly, financial firms have exceptionally high leverage and record revenues differently compared to non-financial firms. Secondly, it is the common practice in similar research and in accordance with Fama and French (1997). We further exclude *Candy & Soda*, *Defence* and *Shipping Containers* due to lack of comprehensive historical financial and stock data. The total number of industry groups in the final sample is 39.

Table 3: Sample construction procedure – sample containing M&A bids

	Observations
Total number of M&A bids by Nordic firms	33 824
Non-listed firms	-22 770
Deal value below $10M	-8 506
Match sample with M&A bids	**2 548**
Diversifying bids	+1 151
Financial industries	- 846
Industries: other and missing data	-47
Final matched sample with M&A bids	**2 806**

The second dataset includes historical financial information from every publicly listed firm in the Nordics. The information required to complete the panel data is total revenue, the total number of employees, EBIT, net income, total assets, total equity, capital expenditures, net PPE, R&D and intangible assets. We cross-reference the sample with the stock-based data in order to include the market-to-book ratio of each firm. We exclude firms that recorded negative revenue and firms in industry groups excluded in the sample containing the M&A bids. The final sample consists of 19 378 firm-year observations, and from this sample, we calculate the median for each variable and industry-year. Furthermore, the panel data sorted by industry groups and industry-years is cross-referenced with the results from the merger identification process to create a dummy variable for pre-wave industry-years.

The third sample contains the dividend adjusted one-year return for each publicly listed firm in the Nordics. The total number of firm-year observations is 16 604. We calculate the median 1-, 2- and 3-year returns for each industry-year and their respective standard deviations from this dataset. This sample is cross-referenced with the results from the merger identification process to classify the pre-wave years.

3.5 Robustness tests and other considerations

To examine the robustness of the results we perform six robustness tests and change fundamental assumptions in the models. (i) Firstly we evaluate the reliability of our method by changing the minimum deal value in the M&A bids in the sample to $1M and $50M. (ii) We change the industry classification and use the 30 industry groups presented by Fama and French (1997). (iii) In the final sample used, we include outliers as industry shocks to generate observations with abnormal values. To test the reliability of this assumption we exclude outliers. We define outliers as observations that deviate with more than three interquartile ranges below the first quartile or above the third quartile. (iv) The standard errors in the logit regressions presented above are clustered by industry, meaning we allow industry-years within an industry to correlate. To test the robustness of this assumption, we run all regressions assuming all observations are independent. (v) To evaluate if variable bias exists between the main independent variable and the added control variables, we run the regressions related to the neoclassical theory by adding the control variables one by one. (vi) Lastly, to examine the relationship between the independent variables, we perform a multicollinearity test. The presence of multicollinearity increases the risk of unreliable and unstable estimates of coefficients. We use the Variance Inflation Factors (VIF) to detect if the independent variables experience high levels of multicollinearity. VIF estimates how exaggerated the variance of a coefficient is because of linear dependence with other predictors. A value of 1 indicates that the variable does not correlate with other independent variables. According to general practice, values below 10 are deemed acceptable (O'brien, 2007).

4. Empirical Results and Analysis

In section 4.1, we present the results and analysis related to the first hypothesis. In the following sections, 4.2, 4.3 and 4.4, we present descriptive statistics, results and analysis of the univariate test and logit regressions, which are applied to test the second and third hypotheses.

4.1 Merger wave identification

To identify merger waves, we employ the method described in section 3.1. For each of the 39 industry groups, we derive the 24-month period with the highest concentration of M&A bids in each decade.

4.1.1 Descriptive statistics

As seen in Appendix A, the first decade saw the highest level of merger activity with a total of 1 592 merger bids compared to 1 214 in the second decade. Between 2000-2009 the average amount of merger bids per industry-year is 40.82, and 31.13 between 2010-2019. Furthermore, the average peak concentration and the mean concentration during a 24-month period is higher during the first decade. Across the entire sample period, *Business Services, Machinery* and *Communication* has the highest merger activity and *Aircraft, Tobacco Products* and *Precious Metals* the lowest.

4.1.2 Results of the merger identification process

We identify 20 merger waves in the first decade and 12 in the second, resulting in 32 waves across 25 industry groups. Seven industry groups experience a merger wave in both decades: *Business Services, Business Supplies, Communication, Construction, Personal Services, Restaurants Hotels Motels* and *Tobacco Products*. The first decade sees a weighted-average peak concentration during a wave of 38.12%. The average number of merger bids during a merger wave is 21.30 compared to 11.05 for the whole decade. The second decade has a weighted-average peak concentration during a wave of 37.59%, and the average number of merger bids during a merger wave is 17.42 compared to 9.08 for the whole decade. By analysing the timing of our industry-specific merger waves, we find indications towards aggregated waves. We observe that 27 of the 32 identified merger waves in our sample occur between 2000-2001, 2005-2007 and 2016-2018, suggesting these are periods of exceptionally high concentration of merger activity on an aggregate level. Our findings provide evidence for H1, indicating merger waves occur on an industry-level in the Nordic market.

Table 4: Merger waves

Industry	First decade (2000-2009)	Second decade (2010-2019)
Aircraft	2004 - 2005	
Beer & Liquor		2016 - 2017
Business Services	2005 - 2006	2017 - 2018
Business Supplies	2000 - 2001	2010 - 2011
Communication	2004 - 2005	2016 - 2017
Computers	2004 - 2005	
Construction	2000 - 2001	2017 - 2018
Construction Materials	2000 - 2001	
Entertainment	2005 - 2006	
Fabricated Products		2017 - 2018
Food Products	2005 - 2006	
Healthcare		2017 - 2018
Machinery	2006 - 2007	
Personal Services	2006 - 2007	2017 - 2018
Petroleum and Natural Gas	2006 - 2007	
Pharmaceutical Products	2006 - 2007	
Precious Metals	2006 - 2007	
Restaurants, Hotels, Motels	2005 - 2006	2016 - 2017
Retail		2015 - 2016
Rubber and Plastic Products	2005 - 2006	
Shipbuilding, Railroad Equipment	2006 - 2007	
Steel Works Etc	2005 - 2006	
Tobacco Products	2000 - 2001	2017 - 2018
Utilities	2000 - 2001	
Wholesale		2017 - 2018
Total number of waves	**20**	**12**
Merger activity in-wave	21.30	17.42
Mean merger activity	11.05	9.08
Weighted-average peak concentration	38.12%	37.59%

4.2 Descriptive statistics for univariate test and logit regressions

Table 5 shows descriptive statistics for the underlying variables used in the univariate test and the logit regressions. Each observation is a unique industry-year containing the intra-industry median value. Due to missing data for certain industry-years, observations differ across variables. *SG*, *2yr-SG* and *ROA* have higher means during pre-wave years. *NIM* and *R&D* have lower means whilst *EG*, *AT* and *CAPEX* are at similar levels as their means. The variables which differ from their means during pre-wave years have the highest standard deviation in Panel A. In Panel B, we confirm that the returns are higher in pre-wave years whilst the dispersions of those returns remain are at similar levels as the rest of the sample period. *MB* and change in *MB* are higher in pre-wave years. A notable statistic is that the change in *MB* is the only variable with a lower mean but higher median during sample period. Outliers as a result of extreme industry-years could be a possible explanation for this. However, since the variables in Panel A are based on the absolute change, we expect the data to follow a positive skew distribution.

Table 5: Descriptive statistics for the final datasets

	Pre-wave years				Non pre-wave years			
	Obs	Mean	Median	Std. Dev.	Obs	Mean	Median	Std. Dev.
Panel A: Neoclassical								
SG	32	.301	.122	.622	742	.255	.159	.411
2yr-SG	31	.36	.166	.653	740	.278	.182	.397
EG	29	.131	.097	.128	706	.167	.102	.264
NIM	31	.092	.044	.131	737	.34	.035	2.757
ROA	32	.137	.04	.485	742	.058	.043	.074
AT	32	.162	.148	.104	742	.17	.125	.322
CAPEX	31	.099	.077	.069	742	.105	.076	.134
R&D	24	.251	.026	.502	585	.657	.028	7.497
Panel B: Behavioural								
1yr-Return	32	.265	.171	.334	737	.077	.048	.393
2yr-Return	30	.421	.39	.671	730	.188	.096	.665
3yr-Return	30	.473	.402	.842	719	.326	.128	1.299
σ(1yr-Return)	28	.605	.437	.498	690	.566	.422	.623
σ(2yr-Return)	26	.931	.662	.674	677	.921	.656	1.216
σ(3yr-Return)	26	1.331	.899	1.5	661	1.248	.799	1.855
Panel C: Market-to-Book								
MB	32	2.117	1.966	1.076	740	1.784	1.591	1.111
σ(MB)	29	4.652	3.416	5.425	723	12.182	2.263	92.036
ΔMB	31	.141	.164	1.475	740	-.025	.006	.655

4.3 Univariate analysis

4.3.1 Analysis of variables in pre-wave years

Using the model specified in section 3.2.1, we examine the sets of factors predicted by the neoclassical and behavioural theories. As seen in Table 6, all variables except *SG* in Panel A have higher ranks than the null hypothesis of 2.5 in pre-wave years.[1] However, only *R&D* shows a significantly higher rank, being significant at a level of 0.01. A notable statistic is that *SG* has a mean rank well below its time-series mean and a high p-value. Panel B shows that all variables except the dispersion of the one-year return are higher in pre-wave years. Only two variables are significantly higher than their time-series mean rank. *1yr-Return* is significant at a level of 0.01, and *σ(2yr-Return)* is significant at 0.05. Panel C shows

[1] Further test of the non-tabulated variables *EBITDA-margin, EBIT-margin, Return on Equity* and *Cash Flow from Operating activities over Sales* yield similar results as *SG*, being lower than their mean during pre-wave years but not significant.

that all variables related to market-to-book were abnormally high in industry-years before a merger wave. *MB* and change in *MB* are significant at a level of 0.01 and 0.05, respectively.

Table 6: Univariate test – The rank of the variables in pre-wave years

	obs	Mean	St Err	t value	p value
Panel A: Neoclassical					
SG	32	2.281	.186	-1.173	.875
2yr-SG	31	2.613	.19	.596	.278
EG	29	2.551	.196	.264	.397
NIM	31	2.678	.214	.828	.207
ROA	32	2.594	.214	.436	.333
AT	32	2.563	.196	.32	.376
CAPEX	24	3.042	.195	2.78	.005***
R&D	31	2.742	.217	1.113	.137
Panel B: Behavioural					
1yr-Return	32	2.969	.165	2.843	.004***
2yr-Return	30	2.767	.218	1.223	.116
3yr-Return	30	2.567	.202	.331	.372
σ(1yr-Return)	28	2.357	.22	-.651	.740
σ(2yr-Return)	26	2.846	.154	2.25	.017**
σ(3yr-Return)	26	2.731	.204	1.13	.135
Panel C: Market-to-Book					
MB	32	2.969	.176	2.653	.006***
σ(MB)	29	2.724	.21	1.068	.147
ΔMB	31	2.871	.166	2.241	.016**

Notes: For all variables, the number presented in this table is the mean rank, across all industries, of the industry-specific rank of the variables in the pre-wave year. We perform a test on the average difference between a rank of 2.5 (middle) and the ranking of the pre-wave year within its industry time-series. The p-values presented in the last column, *, **, and ***, indicate the significance levels of 0.1, 0.05 and 0.01.

The significant increase in *R&D* might result from firms sensing a shift in industry characteristics or structure, meaning further investments or cost cuttings are required to take advantage of the potential shock experienced by the industry. The result from *R&D* is in line with the prediction made by the neoclassical theory. However, a shock should alter the industry characteristics and firms operating environment. Therefore we expect multiple variables to significantly correlate with merger waves to conclude that a shock has occurred and triggered firms to increase merger activity.

Furthermore, *MB* is significant at 0.01 and included as proxies in both theories. *MB* proxies for capital liquidity constraints in the neoclassical theory. The prediction being that higher *MB* values indicate periods where constraints are relaxed and an increase in the ease of financing, implying a surge in merger activity due to lower transaction costs. *MB* further proxies for overvaluation and the degree of optimism in the market. In combination with the significant change in *MB*, the results could imply a positive correlation between overvaluation and clustering of merger activity. The standard deviation of *MB* is not significantly different from the mean rank of 2.5 indicating that intra-industry dispersion in valuation does not correlate with increased merger intensity, contrary to the predictions of both theories. However, the results do not show the overall dispersion in valuation. A possible explanation could be that the firms in relatively high valued industries acquire firms in relatively low valued industries, or vice versa, meaning that cross-industry dispersion in valuations increase the number of diversifying mergers. The results are difficult to interpret as all variables are ranks of intra-industry medians, which is a limitation in the methodology used. Against this background, the univariate test does not conclusively indicate that the neoclassical theory of merger waves hold in our sample.

1yr-Return and *σ(2yr-Return)* are abnormally high and connected to the behavioural theory. The results imply that high stock returns and valuations correlate with pre-wave years. These results are in accordance with the behavioural theory. The stock price increase in pre-wave years suggests that a stock market boom on an industry level could indicate that merger activity will increase, resulting in a merger wave. The dispersion in the long-run return between firms within an industry is significant, possibly providing evidence that differences in intra-industry returns lead to merger waves. Further, we find indications of the explanatory power of the behavioural hypothesis in *MB*, where higher valuations coincide with pre-wave years. Nonetheless, higher valuations in an industry do not equal overvaluation. Firms in examined industries could experience industry-wide or aggregate economic shocks, increasing expectations on future cash flows and deserving of a higher valuation.

4.3.1 Test of the transaction medium

The neoclassical and behavioural theories make different predictions regarding transaction medium during wave years. To test for the difference between wave years and any given industry-year, we employ the t-test specified in section 3.2. The cross-industry mean during the whole sample period is 24.56%, compared to 18.10% during merger waves, implying a relative decline in the frequency of stock mergers during wave periods.

Table 7: Results from t-test

	obs	Mean	St Err	t value	p value
FSM	242	.181	.022	-3.029	.003***

Notes: The mean presented is the mean frequency of stock mergers as a frequency of total mergers in wave-years. We perform a test on the difference between the mean in wave years and the mean of the entire sample. The null hypothesis is that the difference between the mean in wave-years and the mean in the entire sample is equal to zero. The p-value presented in the last column, ***, indicate a significance level of 0.01.

The p-value of 0.003 implies a significant difference between the frequency of stock mergers in wave-years and the mean. Stock mergers are significantly less common during wave years than the mean. This result stands in contrast to the behavioural theory which predicts an overrepresentation of stock mergers in a wave. The use of cash as a transaction medium could have been financed by possibly overvalued equity. With the datasets used, we cannot observe if a shares issue has occurred to finance an upcoming acquisition. However, the relative increase in cash mergers could imply a positive correlation between high capital liquidity, lowering transaction costs, and merger waves. Consequently, the results provide evidence towards H2 and the neoclassical theory.

4.4 Logit regressions

In this section, we apply the logit models described in section 3.3.3. The logit regression models are used to predict when an industry will have a merger wave. We analyse the period between 1999-2018, as these are potential pre-wave years. We present the results for the four models in Table 8. The dependent variable in each of these regressions is *Wave Start*, a dummy variable equal to one if the industry-year is the start of a merger wave.

In the regression of *MB* on *Wave Start*, we find that *MB* has a positive coefficient but not significant, indicating that overvaluation on a stand-alone basis does not explain merger waves. In the second regression, we find that the coefficients of *MB* and *1yr-Return* are positive, while those variables' dispersions have a negative coefficient. The negative coefficients stand in contrast to both the behavioural theory and the neoclassical q-theory, strengthening the implications of the results from the univariate test. However, the coefficients are not statistically significant, meaning they have not statistical impact on the regression. This implies dispersions in intra-industry valuation and stock returns do not explain the occurrence of merger waves. The only variable with a significant coefficient is *1yr-Return*, with a value of 1.604 and a p-value of 0.001. These results indicate that periods following industry-years with high returns are more likely to be merger waves. However, stock returns by themselves are not a good proxy for overvaluation, but could proxy for increased market optimism and indicate that acquiring managers take advantage of short-term share price fluctuations to reallocate assets through M&A. The prediction model has a correlation of 0.072 with the empirical data and significant at 0.01. Nonetheless, the increase in stock returns could be a result of an industry shock, resulting in an increase in market optimism and expectations on future cash flows.

To investigate if an industry shock is the fundamental driver of merger waves, we present the third logit model without the control variables in column (3). In the regression of *ESI* on *Wave Start*, the coefficient 0.053 is not statistically significant, suggesting that ESI on a stand-alone basis cannot predict merger waves. In the following regression of *ESI* on *Wave Start* controlling for *RS*, *TC* and the interaction variable *ESI×TC,* we find that *ESI* has a coefficient of 0.410, which is significant at a level of 0.05. The coefficients of the control variables are in line with the predictions made by the neoclassical theory. The interaction variable has a coefficient of -0.601 significant at 0.1, indicating that sufficient capital liquidity is needed for industry shocks to correlate with the start of merger waves. However, the logit model as a whole is not significant.

The combined logit model shows that *MB* has a coefficient of 0.400 and is significant at 0.1 when interacted with the variables related to both theories. *1yr-Return* has a coefficient of 1.666, which is significant at 0.01, implying that high stock returns precede the start of merger waves. The dispersions of the variables mentioned above have a coefficient close to zero. However, the ranges of values these variables take on are between 0.044 and 1625.65, justifying the low coefficients. A notable observation is that the coefficients are negative; however, neither of the coefficients are significant meaning they are not statistically different from zero. *ESI* is significant at 0.01 with a coefficient of 0.549. The sign of the coefficient suggests that an economic shock coincides with the industry-years preceding merger waves. The interaction variable *ESI×TC* has a coefficient of -0.864, which is significant at 0.05, indicating that high capital liquidity, combined with economic shocks, can help predict merger waves. *RS* and *TC* have a negative and positive coefficient, respectively, which stands in contrasts to the predictions made by the neoclassical theory. Nonetheless, the high p-values contribute to large confidence intervals, making it difficult to interpret the results. The combined logit model has the highest pseudo R^2 and prediction correlation with the empirical data statistically of 0.139 which is significant at 0.05, indicating that the model has the highest explanatory power.

The fact that *MB* predicts merger waves is generally cited as evidence in favor of the behavioral hypothesis. However, as the neoclassical predictors in the form of *ESI* and *ESI*×*TC* are both significant, it may indicate that *MB* and *1yr-Return* is actually proxying for low capital liquidity constraints and hence lower transaction costs which are necessary, but not sufficient on a stand-alone basis, to generate merger waves. As we base the *ESI* on absolute values, we cannot distinguish between positive and negative shocks by observing the index on a stand-alone basis. However, the neoclassical theory does not make predictions regarding the direction of the shock. Further, *MB* and *1yr-Return* are both significant and affect *Wave Start* positively, implying that the shocks experienced by industries in the pre-wave years are positive. Against the background of this, distinguishing between the two theories is challenging. However, a key prediction made by the behavioural theory is that the frequency of stock mergers should increase. We find the opposite. Merger waves correlate with periods of lower relative frequency stock mergers. As the behavioural theory cannot explain this outcome, unless the acquirer is not overvalued and cash is in abundance, our results indicate that the neoclassical theory best explains merger waves on an industry level in the Nordics.

Based on these results, we believe that a positive economic shock triggers or coincides with a stock market boom during periods of high capital liquidity, driving merger waves. In the context of our two competing theories, the results are somewhat ambiguous. Both theories hold explanatory power in our sample. However, our interpretation of these results are that economic shocks are needed in order to produce the market conditions required to generate a merger wave. Hence, we confirm H2 but cannot entirely reject H3.

Table 8: Logit regression models

Variables	(1) Market-to-Book	(2) Behavioural theory	(3) ESI (Without control variables)	(4) ESI (With control variables)	(5) Combined model
MB $_{t-1}$	0.151	0.164			0.400*
	(0.116)	(0.101)			(0.063)
σ(MB) $_{t-1}$		-0.009			-0.020
		(0.426)			(0.331)
1yr-Return $_{t-1}$		1.604***			1.666***
		(0.001)			(0.006)
σ(1yr-Return) $_{t-1}$		-0.476			-0.182
		(0.325)			(0.750)
ESI $_{t-1}$			0.053	0.410**	0.549***
			(0.682)	(0.039)	(0.003)
RS $_{t-1}$				0.521	-0.315
				(0.366)	(0.681)
TC $_{t-1}$				-0.472	0.331
				(0.463)	(0.683)
(ESI×TC) $_{t-1}$				-0.601*	-0.864**
				(0.088)	(0.039)
Constant	-3.439***	-3.457***	-3.176***	-3.428***	-4.041***
	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)
Observations	772	706	598	598	562
Pseudo R2	0.007	0.046	<0.001	0.016	0.079
Prediction correlation	0.028	0.072***	0.009	0.063	0.139**

Notes: This table presents the results for the four logit regression models with the dependent dummy variable *Wave Start*. The variable takes on the value 1 if the industry-year is the start of a merger wave. Column (1) is a regression on *MB*. In column (2) contains the results from a regression with the full behavioural model. In columns (3) and (4), we test the variables related to the neoclassical theory, without and with control variables. In the last column (5), we present the regression results from the combined model. In each regression, we cluster standard errors by industry. The number of observations in each regression differs since comprehensive data on some variables lack for certain industry-years. In the last row, we present the correlation between the models' prediction of wave-years and actual wave-years. The p-values presented in parentheses below the coefficients, *, **, and ***, indicate the significance levels of 0.1, 0.05 and 0.01.

4.5 Robustness test and other considerations

We evaluate the robustness of the results by various robustness tests and change different assumptions in the univariate test and logit regression models. Similar studies on the US market have set the minimum deal value to $50M instead of $10M. We perform all tests and regressions using the higher deal values. The implications of these tests are similar to the presented results, however, they are not as conclusive due to the smaller amount of observations. As presented in Appendix B, we perform all tests and regressions, allowing for $1M or greater bids. The outcome of these tests differs from the results presented in section 4.3 and 4.4. The firm-specific observation does not change; however, the timing and number of merger waves do. The total number of merger bids are 4 059 and the number of identified merger waves is 26. In the univariate test *AT*, *3yr-Return* and *σ(3yr-Return)* become significantly higher in pre-wave years, in combination with *R&D, 1yr-Return, σ(2yr-Return), MB* and Δ*MB*.

In contrast to larger deals, the implication of these results indicates towards the behavioural theory. The logit regressions show that only ESI on a stand-alone basis is significant for the models related to the neoclassical theory. The logit model tailored for the behavioural theory makes predictions with the highest correlation to actual merger waves. In the combined model, dispersions in valuation and stock returns seem to be the major drivers of clustered merger activity. The results strengthen the support for the behavioural theory due to the significant increase of stock mergers during the identified merger waves and the capital liquidity argument does not seem to hold when considering smaller transactions. The differences could be due to the clustering of micro-transactions rather than clustering of major merger activity in specific industries. The micro-transactions appear to cluster when the dispersion in valuation is high, whilst more sizeable M&A deals cluster due to economic shocks during periods of high capital liquidity, which spark stock market booms to create merger waves. We note that our results are sensitive in this regard. However, we argue that the larger deals reflect the general market conditions better, especially since all acquirers are publicly listed firms.

To test the importance of the industry classification, we perform all tests and regression using the Fama and French 30 industry group classification. This industry classification merges similar industries from the 48 industry groups into larger, less strictly defined industries. Changing our baseline model in this regard did not yield significantly different results. The results might indicate that economic shocks affect multiple, closely connected, industries simultaneously, which is reflected by merging similar industries with the new classification and the fact that the merger waves seem to cluster in time.

Furthermore, in the results presented above, outliers are not excluded since we expect industry shocks to affect the variables abnormally. Excluding the outliers from the sample did result in similar outcomes as presented in section 4.3 and 4.4. Since the variables are based on the median in each industry-year, this outcome is expected and we conclude that our tests and models are not sensitive in this regard.

The standard errors in the logit regressions presented above are clustered by industry, meaning we allow industry-years within an industry to correlate. To test the robustness of this assumption, we run all regressions with the assumption that all observations are independent. The implication of the results produced remains the same. However, in the model connected to the neoclassical theory, no variable shows a statistically significant coefficient. The outcome implies that shocks affect industries differently, implying industry structure and characteristics must be accounted for. Therefore, it is reasonable to cluster the standard errors by industry.

Moreover, the regressions related to the neoclassical theory were tested by adding the control variables one by one to check for variable bias between the main independent variable and the added control variables. As presented in Appendix C, the regression of *ESI* on *Wave Start* on a stand-alone basis is not significant. We continue by adding *RS* and *TC*, which yields similar results. However, when we add $ESI \times TC$, *ESI* is significant. The interaction variable's introduction implies that the occurrence of merger waves depends on high capital liquidity and a large unexplained variability exists. Without allowing *ESI* to interact with *TC*, it becomes difficult to observe *ESI's* correlation with merger waves. Therefore, we include all control variables in the neoclassical logit regression model.

Lastly, to examine the relationship between the independent variables, we perform a multicollinearity test, in the form of examining the VIFs of the variables. As presented in Appendix D, the variables with higher VIF values are control variables or products of variables included in the model. Hence, we can conclude that the independent variables do not experience multicollinearity. The PCA used to compute the *ESI* further reduces the risk of multicollinearity since the multiple variables used to compute it might experience high collinearity if used together in a logit model.

5. Discussion

5.1 Discussion of results

As far as we know, there is no previous study on industry-specific merger waves and the driving forces behind them in the Nordics, making it difficult to compare the results. However, several empirical studies have analysed the phenomenon in other markets and periods. In previous literature, the definition of and the method used to identify merger waves varies. As a result of this, no consensus exists as to what drives these waves. We base our definition of a merger wave and the methodology to identify its drivers, primarily on the studies of Mitchell and Mulherin (1996) and Harford (2005). Both papers investigate the US market in the 1980's and 1990's and find evidence for the neoclassical theory. Our findings are similar to these papers, which may be because of methodological reasons. In accordance with the papers mentioned above, as well as the findings of Rhodes-Kropf et al. (2005), we find that merger activity clusters on an industry level.

Mitchell and Mulherin (1996) use sales and employee growth to proxy for industry shocks. They find that the in industries which experienced distinct shocks merger waves were more likely to occur. In our univariate analysis neither sales growth nor employee growth are significantly abnormally high prior to merger waves. However, as our results suggests that an industry shock is necessary to generate waves, we conclude our findings share the same implications as Mitchell and Mulherin (1996). Moreover, we conclude that capital liquidity is an integral component in explaining industry level merger waves. The argument is proposed by Harford (2005) and our findings strengthens the notion that abundant capital liquidity is necessary for industry shocks to result in merger waves. However, in contrast to the findings of Harford (2005) we find that the industry shocks additionally need to coincide with a surge in stock returns and high valuations to increase merger intensity. He concludes that the variables used as proxies for the behavioural theory actually policies for capital liquidity constraints. If this is holds true, we should reject H3. However, since we include proxies for those constraints in the insignificant neoclassical logit model, we conclude that the increase in merger activity is not solely explained by economic shocks and low capital liquidity constraints.

Gugler et al. (2012) reject the industry shock theory, a significant part of the neoclassical theory, by distinguishing between listed and private companies. They found that private companies did not participate in increased merger activity, whilst listed companies did when market optimism and valuation were high. Our sample only consists of listed firms making a direct comparison difficult. Nonetheless, our findings are similar in the regard that listed firms engage in increased merger activity during periods of stock market booms. The key difference being that an economic shock, interacted with periods of high capital liquidity, must coincide to produce waves. The problem which arises is the difficulty to observe the direction of the causality between shocks and stock market conditions. Our conclusion is based on the notion that significant advances in an industry resulting from a shock correlates with stock market surges. We are a aware that this assumption has a great impact on our findings, and that they could be sensitive to the methodology used. However, as our results imply a relationship between industry shocks and stock market conditions correlates with waves, private firms may not participate in these industry merger waves due to their absence from the stock market.

Rhodes-Kropf et al. (2005) use the methodology used by Harford (2005) to identify merger waves. In contrast to our findings, they find that large discrepancies in market-to-book ratios positively correlates with merger waves. They attribute the majority of the increased merger intensity to the degree of misvaluation which in turn creates discrepancies in valuations. Our results do not suggests that dispersions in intra-industry valuations drive industry merger waves. However, they conclude that the industry shock theory has explanatory power since shocks generate merger waves. The reasoning for attributing misvaluation as the driver stems from the finding that firms with high valuations errors are overrepresented as acquirers in merger waves. Due to scope limitations we cannot distinguish between the degree of valuation errors amongst firm but conclude that the fundamental findings are that shocks need to interact with factors related to the behavioural theory.

The overvaluation theory's main prediction is that during periods of stock market booms and subsequent times of overvaluation, the degree of stock mergers should increase due to managers trading overvalued equity for asset (Schleifer and Vishny, 2003). The theory cannot explain the clustering of mergers with other transaction mediums. One of the key findings in our study that suggest the neoclassical theory as the main driver of merger waves, is that the frequency of stock mergers decreases in wave periods. However, as noted by Gugler et al. (2012), the managerial discretion theory states that firms which are not overvalued still engage in M&A if cash is in abundance, or if debt-financing constraints are lower. Our findings are in line with the latter, suggesting that the behavioural theory holds some explanatory power. Due to scope limitations, we do not examine if the acquirer's level of overvaluation or post-merger their returns, which if examined should provide further indications whether the managerial discretion theory holds.

5.2 Considerations regarding Economic Shock Index (*ESI)*

To account for multicollinearity between the economic shocks proxies, Harford (2005) uses an index composed of the first principal components derived from a PCA. After analysing the multicollinearity between our proxies, we conclude that no correlation is considered too high. While it may not be necessary given low correlations, we follow Harford (2005) and derive an economic shock index (*ESI*). The reasoning being to compress the multiple proxies into one single entity used in the logit regression models. However, our methodology differs to a certain extent since we choose to include principal components with eigenvalues above 1 and weigh them by their explained variance. The procedure captures as much of the variance in the underlying proxies as possible. We argue that it is reasonable to include multiple principal components, as the first principal component only accounts for 28.4% of the underlying variance, whilst the three components together account for 61.2%. Furthermore, it is common practice to include components with eigenvalues above 1 when deriving indices from PCA.

Although the variables are standardised prior to the PCA, their variance could differ in size. The variables with the highest variance will have a more significant impact on *ESI*. We apply an orthogonal varimax rotation to account for this. The rotation increases variables loadings on one component while minimises it on other components. By doing this, we equalise the effect each variable has on the index. Nonetheless, in the univariate test, only *R&D* is significant. However, shocks should alter industry characteristics, and the theory makes no prediction regarding which factors are affected. Therefore, we argue that it is sensible to include all the variables in the index and construct it with a PCA.

To the best of our knowledge, similar studies do not share the methodology of weighing principal components and therefore risk some validity of our results. Nonetheless, given the widespread use in other research fields and the fact that the coefficient of *ESI* in the regressions is similar to the coefficient of the index used by Harford (2005), we argue that it is a reliable proxy for economic shocks.

6. Conclusion

In our study, we aim to investigate if merger waves are present on an industry-level in the Nordics and what underlying factors drive these waves. We conduct simulations of the empirical distribution of merger activity, t-tests and regressions of logit models to address this research question. Further, we propose the use of an index, based on principal component analysis of key operating performance measures, to capture economic shocks.

We confirm our first hypothesis by concluding that the Nordic M&A market is characterised by clustering in merger activity on an industry level. In total, we identify 32 merger waves across 25 industries. A notable statistic is that these waves appear to cluster in time. 27 of the 32 identified waves occur during 2000-2001, 2005-2007 and 2016-2018, suggesting these are periods of considerably increased merger activity. The clustering of these industry waves may potentially be aggregated merger waves.

The two competing theories regarding the drivers of merger waves are the neoclassical, which states that waves occur due to shocks, and the behavioural which relies on stock market booms and overvaluation to explain the existence of waves. Based on our tests and regression models, we can conclude that both theories have explanatory power in our sample. However, the predictions made by the neoclassical theory best fit the empirical evidence from the Nordic market. Our findings suggest that economic shocks are needed to produce the market conditions required to generate an increase in merger intensity. However, shocks on a stand-alone basis are not sufficient. High capital liquidity must be present for firms to engage in increased merger activity as a response to the industry shock. A key prediction made by the behavioural theory is that the frequency of stock mergers should increase during a merger wave as result of managers trading overvalued equity for assets. We find the opposite to be true. Nevertheless, we argue that stock market conditions are important in explaining occurrence of merger waves. Hence, our findings suggest the existence of a complex relationship between merger waves and economic shocks, capital liquidity constraints, and stock market booms. In conclusion, we find evidence for the neoclassical theory of merger waves, indicating economic shocks are the fundamental drivers of merger waves on an industry level in the Nordics even though we cannot fully reject the behavioural theory.

The notion of mergers occurring in waves is virtually undisputed, yet there is no clear consensus as to what drives these waves. Our research is of particular interest to investors and managers of firms engaging in M&A activity. Using the implications from our study, firms can reposition themselves in anticipation of demand shocks to take full advantage of periods with intense merger activity. Furthermore, our thesis is relevant for researchers investigating merger waves in the Nordics due to the scarcity of previous research. Previous studies in other markets come to different conclusions, providing evidence for both the neoclassical and the behavioural theory. To the best of our knowledge, our research on industry level merger waves in the Nordics is unique. We contribute to the theoretical framework by exploring the phenomenon in a new context. Our findings provide evidence for the existence of mergers waves on an industry level in the Nordic market and shocks as their fundamental drivers by employing an index proxying for economic shocks.

We acknowledge that there are limitations to our study. The sample contains identified merger waves that occurred during industry-years lacking comprehensive data. Due to this, even though we have identified 32 merger waves, all tests and regressions do not share the same number of observations. However, all variables are industry-specific, limiting the effect on the results. Nevertheless, we recognise this has implications on the reliability of the results. An industry shock is not directly observable, meaning increased reliability on proxies. We acknowledge this has implications on our results, but are confident in the proxies used in the study. Further, as post-merger returns are not included in the analysis, we cannot test all predictions made by the underlying theories.

The process of developing and performing our study has shed light on several areas we believe to be of particular interest for further research. First of all, the neoclassical and behavioural theory consists of various underlying theories. The q-theory, industry shock theory, managerial discretion theory and overvaluation theory are based on different assumptions and make different predictions. Detailed research may provide evidence for either, or a combination, of the theories above. Additionally, one of the predictions made by the behavioural hypothesis is that long-run returns will be poor following waves, either because of misperceived synergies, firm-specific valuation errors or managers engaging in wealth-destroying mergers. Therefore, further research could analyse the long-run returns of the bidders following merger waves and find increased support for or against the behavioural theory. Due to scope limitations, we do not study aggregated merger waves. By analysing the timing of our industry-specific merger waves, we find indications towards aggregated waves. We observe that the majority of waves in our sample occur between 2000-2001, 2005-2007 and 2016-2018, suggesting these are periods of exceptionally high concentration of merger activity on an aggregate level. Further research in the Nordics may confirm or reject the conjecture that aggregated merger waves occur in the Nordic market, and whatever their fundamental drivers may be.

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Appendix

Appendix A: Descriptive statistics M&A bids

	First decade (2000-2009)				Second decade (2010-2019)			
	Merger bids	Peak	Peak (%)	Mean	Merger bids	Peak	Peak (%)	Mean
Agriculture	17	7	41%	3,7	24	8	33%	4,6
Aircraft	1	1	100%	0,2	0	0	-	0,0
Apparel	5	2	40%	1,1	4	2	50%	1,0
Automobiles and Trucks	28	11	39%	5,5	18	6	33%	3,8
Beer & Liquor	12	5	42%	2,3	4	3	75%	0,9
Business Services	334	106	32%	64,9	274	83	30%	52,5
Business Supplies	62	25	40%	11,4	32	13	41%	5,9
Chemicals	37	14	38%	7,4	46	13	28%	8,6
Communication	118	44	37%	23,8	61	23	38%	12,9
Computers	35	16	46%	7,3	7	3	43%	1,2
Construction	43	17	40%	7,6	45	20	44%	9,1
Construction Materials	82	27	33%	15,0	55	17	31%	9,8
Consumer Goods	11	4	36%	2,2	26	9	35%	5,4
Electrical Equipment	17	7	41%	3,6	15	6	40%	2,6
Electronic Equipment	57	18	32%	10,8	33	12	36%	6,9
Entertainment	6	5	83%	1,3	13	5	38%	2,7
Fabricated Products	7	3	43%	1,1	10	7	70%	1,9
Food Products	38	19	50%	9,0	35	11	31%	7,0
Healthcare	12	5	42%	2,8	18	12	67%	3,6
Machinery	114	41	36%	23,2	76	20	26%	14,5
Measuring and Control Equipment	20	7	35%	4,2	13	4	31%	2,4
Medical Equipment	35	12	34%	7,1	27	8	30%	5,4
Non-Metallic and Industrial Metal Mining	4	1	25%	0,7	8	4	50%	1,4
Personal Services	13	7	54%	2,6	9	6	67%	1,7
Petroleum and Natural Gas	73	31	42%	15,7	38	13	34%	7,5
Pharmaceutical Products	51	23	45%	10,5	78	23	29%	14,7
Precious Metals	3	3	100%	0,6	5	2	40%	0,8
Printing and Publishing	33	12	36%	6,4	22	9	41%	4,5
Recreation	19	8	42%	4,0	10	5	50%	2,1
Restaraunts, Hotels, Motels	23	10	43%	4,5	20	9	45%	4,0
Retail	28	9	32%	5,3	22	10	45%	4,7
Rubber and Plastic Products	16	8	50%	3,6	15	6	40%	3,0
Shipbuilding, Railroad Equipment	24	12	50%	4,8	4	2	50%	0,8
Steel Works Etc	44	16	36%	8,4	22	9	41%	3,8
Textiles	4	2	50%	0,7	7	3	43%	1,5
Tobacco Products	2	2	100%	0,0	2	2	100%	0,3
Transportation	68	21	31%	13,8	43	12	28%	7,9
Utilities	33	13	39%	6,5	14	5	36%	2,7
Wholesale	63	19	30%	11,5	59	21	36%	11,5
Total number of merger bids	1592				1214			
Cross-industry weighted average mean	40.82	15,2	37,2%	8,1	31.13	10,9	35,1%	6,0

Appendix B: Robustness test using minimum deal value $1M

Univariate Test

	obs	Mean	St Err	t value	p value
Panel A: Neoclassical					
SG	26	2.538	.224	.172	.432
2yr-SG	26	2.731	.211	1.091	.143
EMP	24	2.417	.24	-.347	.634
NIM	25	2.52	.193	.104	.459
AT	26	2.808	.208	1.482	.076*
ROA	26	2.692	.227	.847	.203
R&D	20	3.050	.235	2.342	.015**
CAPEX	26	2.731	.204	1.13	.135
Panel B: Behavioural					
1yr-Return	26	3.077	.2	2.893	.004***
σ (1yr-Return)	22	2.636	.224	.61	.274
2yr-Return	24	2.625	.232	.539	.297
σ (2yr-Return)	21	2.857	.199	1.798	.044**
3yr-Return	24	2.792	.217	1.345	.096*
σ (3yr-Return)	21	2.809	.214	1.446	.082*
Panel C: Market-to-Book					
MB	26	3.038	.196	2.748	.006***
σ (MB)	23	2.652	.256	.594	.279
Δ *(MB)*	25	3.12	.145	4.272	<.001***

Notes: In this analysis we allow for M&A bids with deal value equal and above $1M. For all variables, the number presented in this table is the mean rank, across all industries, of the industry-specific rank of the variables in the pre-wave year. A test is performed on the average difference between a rank of 2.5 (middle) and the ranking of the pre-wave year within its own industry time series. The p-value for the hypothesis that the pre-wave ranking is above the middle rank is presented in the last column, *, ** and *** indicate the significance of the difference at a level of 0.1, 0.05 and 0.01.

Logit regression models

	(1)	(2)	(3)	(4)	(5)
Variables	**Market-to-Book**	**Behavioural theory**	**ESI (Without control variables)**	**ESI (With control variables)**	**Combined model**
MB_{t-1}	0.304***	0.380***			0.295
	(<0.001)	(<0.001)			(0.120)
$\sigma(MB)_{t-1}$		0.002**			0.002**
		(0.041)			(0.049)
$1yr\text{-}Return_{t-1}$		0.911*			0.674
		(0.055)			(0.200)
$\sigma(1yr\text{-}Return)_{t-1}$		0.286			0.464**
		(0.276)			(0.011)
ESI_{t-1}			0.236*	0.270	0.255
			(0.056)	(0.145)	(0.195)
RS_{t-1}				0.670	0.154
				(0.232)	(0.823)
TC_{t-1}				-1.322*	-0.966
				(0.062)	(0.279)
$(ESI\times TC)_{t-1}$				-0.059	-0.361
				(0.849)	(0.382)
Constant	-3.973***	-4.681***	-3.391***	-3.192***	-4.047***
	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)
Observations	772	706	598	598	562
Pseudo R2	0.035	0.107	0.008	0.036	0.110
Prediction correlation	0.188***	0.263***	0.040*	0.116	0.260***

Notes: This table presents the results for the four logit regression models with the dependent dummy variable *Wave Start*. The variable takes on the value 1 if the industry-year is the start of a merger wave. Column (1) is a regression on *MB*. In column (2) contains the results from a regression with the full behavioural model. In columns (3) and (4), we test the variables related to the neoclassical theory, without and with control variables. In the last column (5), we present the regression results from the combined model. In each regression, we cluster standard errors by industry. The number of observations in each regression differs since comprehensive data on some variables lack for certain industry-years. In the last row, we present the correlation between the models' prediction of wave-years and actual wave-years. The p-values presented in parentheses below the coefficients, *, **, and ***, indicate the significance levels of 0.1, 0.05 and 0.01.

Appendix C: Robustness test logit model 3, adding controlling variables

Variables	**1**	**2**	**3**	**4**
ESI $_{t-1}$	0.053	0.067	0.075	0.410**
	(0.682)	(0.605)	(0.577)	(0.039)
RS $_{t-1}$		0.210	0.637	0.521
		(0.520)	(0.279)	(0.366)
TC $_{t-1}$			-0.631	-0.472
			(0.336)	(0.463)
(ESI×TC) $_{t-1}$				-0.601*
				(0.088)
Constant	-3.176***	-3.398***	-3.384***	-3.428***
	(<0.001)	(<0.001)	(<0.001)	(<0.001)
Observations	598	598	598	598
Pseudo R2	<0.001	0.001	0.007	0.016
Prediction correlation with merger waves	0.009	0.015	0.052	0.063

Appendix D : Multicollinearity test, VIF

Dependent variable: ***Wave Start***	**VIF**	**1/VIF**
ESI × TC	3.98	0.251
ESI	3.95	0.253
TC	2.08	0.480
RS	1.92	0.522
1yr-Return	1.38	0.723
σ (1yr-Return)	1.22	0.816
σ (MB)	1.21	0.827
MB	1.03	0.974