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How Does Liquidity Drive the Latest M&A Wave? ☆

Minqian Zhang

Department of Finance, Erasmus School of Economics, Rotterdam 3062PA, the Netherlands

Abstract

Previous economists have attributed the aggregate merger and acquisition waves to the neoclassical explanations, in which firms intensively choose to acquire undervalued assets to face changes in the new environment when there is sufficient overall capital liquidity. While many researchers focused on the past six M&A waves, this paper studies the most recent waves in 31 industries after the financial crisis in 2007. On account of the capricious US monetary policies and based on the sticky price theory, this study contends that the rate spread is no longer a reliable proxy for capital liquidity. It proposes a new measure of the industry liquidity — the liquidity ratios. Following the methods of the neoclassical explanations, the study finds that the method of liquidity ratios is more potent than that of rate spread to explain the 7th M&A wave.

Keywords: Merger & Acquisitions, Industry Liquidity, 7th M&A Wave, Takeover, Neoclassic

Name: Minqian Zhang

Student Number: 423674mz

Supervisor: Dr. Ruben de Bliek

Second Assessor: Dr. Joris Kil

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Contents

1. Introduction

While mergers and acquisitions (M&As) have been widely exploited as a crucial corporate strategy for companies seeking for further growth, the phenomenon that remarkable outpourings of M&A activities with massive volume and unprecedented high value often clustered over certain years has arisen interests among economics and finance researchers. Scientific literature has so far characterized six significant M&A waves in the US over a time span of 110 years since 1897.

To date, the general view of those patterns is that these M&A waves are triggered by market conditions and firm behaviors. However, explanations are various and each entails a complete and reasonable story. Roll (1986) attributed M&A waves to managers hubris behavior, whereas some researchers argued the impact of market manias. Meanwhile, finance scholars claim that investor behaviors in stock market play a role: public companies often use overvalued stock as a means of acquiring undervalued assets, especially during stock market surging periods due to the overconfidence of synergies, which coincide with high market-to-book (M/B) ratios (Shleifer & Vishny, 2003; Rhodes-Kropf & Viswanathan, 2004). So far the most recent M&A wave occurred during 2003 and 2007, known as the sixth M&A wave, and was killed by the notorious global financial crisis (GFC).

Although many excellent research papers, assuming the degrees of rationality and efficiency of managers and the market, analyzed the behavioral factors that propel the number of M&A deals made in a certain period, they failed to explain the intriguing fact that all six waves vanished after either a financial crisis or an economic recession. Neoclassical economists believe that the appearances of industry clustering and M&A waves are not unintentional; they have shown that intensive M&A activities are driven by industrial shocks such as changes of macroeconomic, technological, regulatory environments. (Mitchell & Mulherin, 1996). This provides a plausible explanation of not only the drivers but also the turning points of the waves; an industrial shock could possibly spark an M&A wave as well as kill an existing wave, in that the new environment may be uncongenial to restructuring strategies.

Harford (2005) following the idea of the industry shock hypothesis investigates the origins of merger waves and tests the feasibility of the neoclassical explanation and the market timing (behavioral) hypothesis, using firm data from 35 industries over the period 1981–2000. The results seem to be in line with the previous neoclassical explanations yet revealed another explanatory factor — capital liquidity — being a significant determinant to trigger M&A waves even though industrial shocks exist. High overall capital liquidity provides firms with abundant resource of financing so that it gives incentives for the managers to make restructuring strategies such as mergers or acquisitions. Using the difference of the commercial loan rate and the risk-free rate as a proxy for aggregate capital liquidity and plotting the results with the annual average M/B ratios over the period, Harford (2005) concludes that the former is a significant driver of the latter so that the fundamental theory base of the behavioral hypothesis is violated. Thus, the market timing may not be a reliable explanation of industrial merger waves.

The reasoning of neoclassical economists shuts the controversy for a while until Gugler, Mueller, & Weichselbaumer (2012) challenges Harford (2015) through the contradictory results between the mergers within publicly listed firms and mergers within private firms from 1991 to 2004. Contrary to what the 'industry shock' has predicted, the defined industry clustering and merger waves of the listed firms cannot be examined simultaneously among the unlisted firms. According to Gugler et al. (2012), if the industry shock hypothesis were true, that shocks were supposed to affect the economy as a whole, they would have made mergers profitable for all companies so that there should have been merger waves for unlisted firms as well.

However, regardless of the further conclusions Gugler et al. (2012) has made, the method is problematic because simply separating the listed and unlisted firms in order to discriminate the pure effect of stock market causes sample selection bias. Start-ups and private firms go public for better opportunities; listed corporations sustain large access to resources. Corwin & Harris (2001) claims that the more a firm's industry peers are listed, the more likely it will conduct an IPO. This implies that companies in one industry could be intensively listed in a stock exchange, leaving the unlisted ones in the same industry ineffective — listed firms compete violently with one another, whilst unlisted firms struggle to survive. Moreover, the likelihood of IPO grows as the M/B ratio of an industry increases (Pagano, Panetta, & Zingales, 1998), which again confirms the findings of Harford (2005). It is also notable that global integrations and cross-border deals have dominated the data sample of Gugler et al. (2012) over the period 1994 – 2001. As a result, it is reasonable to argue that publicly listed companies are relatively easier to be captured since they disclose more information.

While the dispute remains unsolved, the macroeconomic environment is in the throes of revolution. Proactive monetary policies made by the Federal Reserve and the low-interest rate imposed by the European Central Bank have propelled the recovery of the global market from the GFC in 2007. Over the longest bullish period, 2009 – present, the S&P 500 index has rallied from 730 to almost 2900 since its plunge in 2008. In terms of the M&A market, the industrial integration and manufacturing globalization are subtly raising the numbers of cross-border mergers and acquisitions. Indeed, the booming stock market and the low-interest rate both indicate high overall capital liquidity in the market and thus an emerging M&A wave has been foreseen.

Nevertheless, along with the booming market, the macroeconomic environment has become considerably complex. On the one hand, trade protectionism and the American First initiative by the Trump administration induce many uncertainties concerning the world economy. Since 2014, the Fed has been gradually increasing the interest rate, which makes dollar continually strong and imposes pressures onto domestic companies as well as emerging economies. Meanwhile, the oil price doubled since 2015. Oil price affects the costs of various industries. Hence, macroeconomic figures have indicated low capital liquidity. On the other hand, M&A is no longer an uncharted topic. Massive corporate M&A cases have made managers assess the pros and cons of a M&A transaction more and more sophisticatedly, regarding valuation, timing and payment methods. Inevitably, M&A deals made after the GFC, more specifically between 2010 and onwards, have created their unique characters. According to data given by FactSet, in both 2014 and 2018, the M&A market has recorded higher numbers of deals over $1 Billion than the number of deals in any year. The total deal value in 2018, despite with only ten months, has already topped all of the values in 21 years before 2007. Thus, it is clear that a new M&A wave is stirring.

Given the characters peculiar to this emerging wave, it is necessary to examine whether the previous concluded neoclassical explanations pertained to 'industry shocks' and the overall 'rate spread' approaches are still plausible. What's more, it is essential to extend the measure of capital liquidity, in that recent market dynamics could mislead the rate spread. As a result, I propose the following research question:

What neoclassical factors, beyond the overall 'rate-spread' proxy for capital liquidity, can better explain the most recent M&A wave?

As Harford suggested at the end of his paper that liquidity ratios may also play a role, I argue that the current ratio and the quick ratio to be potential factors of the waves. This premise is intuitively derived from the analysis of Harford (2005). Again, the theoretical framework of the neoclassical explanations is robust, but the proxy used, the difference between the commercial loan rate and the risk-free rate, may be biased. According to the price stickiness theory, decisions of a firm are reluctant to the price changes of the market in the short run. Managers making takeover decisions depend on the performance of the bidding and the target firms. Although the Discounted Cash Flow (DCF) valuation method is predominated by interest rates, more firms apply Comparable Company Analysis (CCA) method especially for the ones in technology industries. Consequently, average accounting ratios, such as the current ratio and the quick ratio, of an industry can better indicate the capital liquidity of the industry and thus may be significant drivers of industry merger waves.

The rest of this paper is structured as follows: The next section reviews the literature and establishes the hypotheses to be tested. Section 3 covers the data and a detailed explanation of selected variables, followed by sections contain explanations of the applied statistical methods, demonstrations of the results, and discussions about the conclusions.

2. Literature Review and Hypothesis Development

In this section, I will first review the significant findings derived from previous studies. Then, building on those theories, I will present my reasoning, the hypotheses, as well as the motivation behind them.

2.1. Literature Review

It is well acknowledged that six M&A waves exist so far. The first M&A wave (1897 – 1904) surged mainly for monopolies (Kim & Zheng, 2014), the second wave (1916 – 1929) followed the idea of pursuing economies of scale, the third wave (1965 – 1969) and the fourth wave (1984-1989) are driven by the regulations against antitrust and motivations of diversification (Shleifer & Vishny, 1991) , the fifth wave (1994 – 2001) with many cross-border mergers witnessed was triggered by the integration of the global market, and the sixth wave (2003 – 2007) was attributed to the high stock prices and easy access to capital (Alexandridis, Mavrovitis, & Travlos, 2012). Before I continue with the 'industry shock' contentions, let us review on an alternative to the neoclassical explanations.

2.1.1. Behavioral Explanation

The behavioral explanation got its adherents since the 1980s. Chappell & Cheng (1984) proposed that the Tobin's Q ratio motivates managers to make acquisition decisions. Higher Q ratios indicate higher valuation with which firms can acquire others with lower ones. In the meantime, the third and the fourth M&A waves were described as the 'conglomerate wave' and the 'refocusing wave' respectively, both have corresponded with favorable stock market conditions

(DePamphilis, 2015). As a result, M&A waves are explained by speculative behaviors of firm managers accumulated over the period after a bull market as researchers reported correlations between extensive merger activities and stock overvaluation (Golbe & White, 1988).

Many later studies have shown similar results with data over the same periods, among which is Rhodes-Kropf, Robinson, & Viswanathan (2005), an empirical study circulating the study by Rhodes-Kropf et al. (2004) whose results shed light on discovering the actual effect of the Market-to-Book (M/B) ratio instead of Tobin's Q, despite similar to. Thus, the behavioral hypothesis suggests that a M&A wave will be triggered after the appearance of a bull market, following the rising stock prices so that it is called market timing. Nevertheless, Harford (2005) argues that M/B ratios are correlated with overall capital liquidity of the market and thus rejects the hypothesis of market timing.

2.1.2. Neoclassical Explanation

Unlike the market timing hypothesis, the neoclassical explanation assumes that both the managers and the market are rational. The so-called 'industry shock' is a notion of economic disturbance: Whenever there are changes of industry, either good or bad, firms proactively take actions in order to adapt to the new operating environment quickly, and together shift the aggregate demand and supply to a new equilibrium. This idea has been generated since the early time of the neoclassical economics developed. In terms of mergers, change in technology is a significant factor. (Coase, 1937) So far, many industrial factors subject to 'shocks' are found to have impacts on propel merger waves, factors such as new regulations, technological innovations, taxation reforms, etc., concluded by Mitchell et al. (1996). Jovanovic & Rousseau (2001) studied the positive effect of technological factors on the dispersion of the Q ratios and completed the neoclassical story between industry shocks and firms' financial ratios.

The neoclassical explanation is augmented by Harford (2005) who 'suggests a role of capital liquidity of merger waves' and exploits a new 'macro component which proxies for capital liquidity', the rate spread. (pp. 532 & 542) This proxy is justified by the 'Federal Reserve's Senior Loan Officer Opinion Survey' conducted by Lown, Morgan, & Rohatgi (2000, pp.1), where loan officers are tracked constantly in terms of the commercial lending cases under their control. According to Lown et al. (2000) and Harford (2005), following a credit crunch policy, a series of subsequent events are elicited — tightened loan issuance, shrinking investment and production, and predicted low capital liquidity. Thus, in Harford's paper, rate spread is used as a proxy for capital liquidity in any form of the economy. So far, incorporated the rate spread, the neoclassical explanation is well developed: rate spread affects the neoclassical model through capital liquidity. Hence, high capital liquidity, facilitating economic, technological, or regulatory shocks, drives firms taking acquisition decisions in an industry level, meanwhile, overall high liquidity propels several industry waves clustering over the same period resulting in a M&A wave.

2.2. Hypotheses Development

Building on the previous findings, this paper agrees with the neoclassical explanations but intends to challenge the feasibility of the method using the rate spread as a proxy for macro liquidity.

2.2.1. *Market Equilibrium & the Demand*

As I have demonstrated in the previous section, the global market has no longer been the same prior to the GFC. For years, high or low capital liquidity of the market has been enigmatic; Dovis & Kirpalani (2018) shows a figure of the volatile interest rate spread over 10-year bonds of several countries, which confirms the idea of this paper.

One concern about Harford's rate spread method is that it takes only the views of the money supply, whether the rates were taken from either the loan issuer or the central bank, sectors that provide firms with monetary support. Nevertheless, given the neoclassical economic theory, a market equilibrium is determined by aggregate supply and demand, whereas government may exploit monetary instruments or intervene factors of production in order to shift the market to a new equilibrium. If the combinations of interest rate and production resulted in goods market equilibrium (the demand) together with the equilibrium in the money market (the supply) are plotted in a Cartesian coordinates where the total production is the horizontal axis, and the interest rate is the vertical axis, the intercept of the two curves denotes a general market equilibrium and the International Financial Market (IFM) equilibrium in the short run (Burda & Wyplosz, 2013, Chapter 10). This pattern is known as the Investment Saving and Liquidity Money (IS-LM) model. Any changes in the money market will alter the equilibrium, and further shift the LM curve resulting in a new interception with the IFM curve. Subsequently, the IS curve will shift over time until it reaches the new equilibrium. Subsequently, the IS curve will shift over time until it reaches the new equilibrium; it takes time for the market demand to adjust to the new equilibrium.

The interpretation of the IS-LM model is plausible, and it has been further justified by Mankiw (1985) using the Price Stickiness theory, for which he introduced the 'menu cost'. Mankiw gave an example of a restaurant to explain his theory; while the prices of materials such as vegetables, meat, and ingredients change day by day, the price listed on the menu will be constant for a much longer period, usually more than a year, because changing the menu costs money as well. The theory sheds light on understating the time lag between the change in equilibrium and firms reacting to it because changing the 'menu' incurs transaction cost. Following this idea, I contend that managers will stick to their current agenda or strategy regardless of the changes in the money supply. If a company has made a strategic plan focusing on integration and decided to acquire firms to pursue economies of scale, it will not be hasty in changing its plan subject to an increase in the interest rate. The previous studies, to some extent, ignored the perspective of the demand — the real reaction of managers towards a credit crunch.

2.2.2. *Testing Hypotheses*

Building on the neoclassical explanations, this study incorporates the view from the demand side, the side from the perspective of individual firms and argues that liquidity ratios play a role in decision makings of merger or acquisition strategies, since managers make decisions based on the financial reports of the company. Saleem & Rehman (2011) showed that the significant impact of the ratio on a firms return on equity (ROE) and profitability, which drive the M&A waves across various industries simultaneously resulted in aggregate M&A wave in the recent decade. The idea of this paper is to define which of the liquidity ratios play the role by testing a series of hypotheses.

First off, it is necessary to show that merger deals or takeovers frequently happen in recent years after the GFC in 2007. FactSet reported an emerging wave in the United States throughout

2014 – present, from the bar chart illustrating the number of deals from 1998 to 2018. The pattern of 2015 – 2018 resembles that of 2004 – 2007, the sixth wave. Nevertheless, given the overall M&A announced numbers, FactSet failed to provide details with specific industries. Thus I will begin with examining the industries that are associated with significantly large numbers of M&A deals over the period 2008 – 2018. Such industries are defined as industry-with-waves, and thus the first hypothesis is:

H_1*: During the recent decade, there is a period when many industries encountered large number of restructuring activities, more specifically mergers or acquisitions.*

After testing the first hypothesis, certain industries with significant M&A waves, the 'with-wave' industries, will be defined. The next step is to derive applicable liquidity ratios. Liquidity ratios are usually found in a firm's income statement and are used to measure the firm's ability to meet its short-term obligations. Since liquidity ratios are calculated as assets divided by liabilities (i.e., current assets divided by current liabilities for current ratio), a higher ratio indicates a better ability to meet the obligations, meaning that the higher the ratio, the higher capital liquidity a firm has. I further define an industry level liquidity ratio as the weighted average liquidity ratios of all firms operating in one industry. Assuming that these ratios drive the M&A waves, I need to test whether bidding firms in a given 'with-wave' industry have different average current ratios (or quick ratios) in the industry. Therefore, the second hypothesis is:

H_2*: The weighted average liquidity ratios of the bidding firms in a 'with-wave' industry are different from the average level of this industry.*

H_1 and H_2 help to justify the significant phenomenon that great M&A deals are associated with liquidity ratios with unique features. After defining the industry level liquidity ratios of all listed industries, a measure of the market liquidity is proposed in order to test the difference of the liquidity ratios between the 'with-wave' and the 'non-wave' industries. In comparison, I track the rate spread, the proxy for overall capital liquidity, and depict the trend of the rate to examine the consistency. With this, I introduce the third hypothesis:

H_3*: The industry level liquidity ratios of the 'with-wave' industries are higher than those of 'non-wave' industries, whereas rate spread may not.*

Finally, the relation between the liquidity ratios and the aggregate M&A waves is being examined, for which I introduce a binary choice model, the probit model. The proxies I used in this study for the liquidity ratios are the current ratio and the quick ratio. The model is used to estimate the probability of a merger deal or takeover. If, as the ratio increases, the probability grows, a positive effect can be concluded. Thus, the fourth hypothesis is as follow:

H_4*: Current ratio and quick ratio have a significant positive effect on increasing the probability of deciding on a merger or acquisition.*

The testing hypotheses together will address the research question: The first hypothesis provides insights into M&A deals in the most recent decade; The second and the fourth hypotheses give further explanation to the neoclassical views on M&A waves; The third hypothesis examines whether the method of Harford (2005) is plausible, given new economic environment. Furthermore, if the fourth hypothesis cannot be rejected, it suggests that high liquidity ratios propel firms making merger or takeover strategies, which further implies that higher intra-industry liquidity ratio drives firms to merge or takeover and several industries with high liquidity ratios will simultaneously trigger an aggregate M&A wave.

3. Data & Methodology

3.1. Data & Descriptive Statistics

I retrieve data of all mergers and tender offers announced by American publicly listed companies between January 2008 and October 2018 from Thomson One's Securities Data Company (SDC) with a transaction value of at least \$ 100 million as the M&A wave sample. The Standard Industrial Classification (SIC) codes of the bidders and the targets are used to identify the industries. If the bidder and the target are in the same industry (same SIC), the transaction will be counted only once in this industry. If the bidder and the target are in different industries, the deal will be counted for both industries. Then, I compile data of I/B/E/S estimates of historical financial ratios of all publicly listed firms operating in the US market from Wharton Research Data Services (WRDS) in the same period to analyze the market of 85 industries. I use the Committee on Uniform Security Identification Procedures (CUSIP) code to match the financial data with the firms in the M&A wave sample. In addition, the corporate loan rate and the Federal Reserve rate of the period are downloaded from Thomson Reuters.

9578 merger deals or tender offers are collected in the wave sample (sample period Jan. 2008 – Oct. 2018). For the first decade of the wave sample, 2008 – 2017, there are on average 876 M&A deals announced every year; the announced deals in the period 2011 – 2015 are above the average. (See Figure 1.) This figure has climbed throughout the 5-year time span and reached the peak in 2014 with 1120 deals announced, yet hasn't dropped much in 2015 with 1108 recorded deals. To incorporate the most recent records, I select the number of deals of the first 10 months of each year, whose average is 728 deals. In this case, only those in the years 2011, 2013, 2015, 2017, and 2018 are above the average; the figures become discrete. Nevertheless, as I predicted, there seems to be an aggregate M&A wave between 2011 and 2015. Based on Mitchell et al. (1996)'s and Harford (2005)'s studies of wave period, I use the 24-month time span as a wave period.[1]

In terms of the industry level, I further divide the sample into 10 sub-samples according to the SIC code of the bidders and targets. The macro industries are Agriculture, Mining, Construction, Transportation, Wholesale Trade, Retail Trade, Finance & Real Estate, Service, Public Administration, and Manufacturing. Among these industries, Finance & Real Estate, Service, and Manufacturing are the ones with the most M&A deals. It is obvious that some industries encounter fewer M&A transactions than do the others, such as Public Administration with only 5 recorded deals over the decade. One may concern that some industries in the market are relatively small and thus have far fewer merger cases than the bigger ones such as Finance and Manufacturing. Admittedly, the number of deals depends on the number of firms operating in an industry. However, this will not affect the results since aggregate waves are not driven by small industries of the market. In order to cancel out sample selection bias, I apply a method in which waves are defined within a single industry. (See the next section)

Breaking down the macro industry into more specific industries based on the 2-digit SIC code provides us with further insight: Media Service and Health Service together account for 21% of the

[1] If the recorded deals in November and December are eliminated from the sample, there are relatively large numbers of deals recorded every two years (2011, 2013, 2015, and 2018). The two-year wave period coincides with the 10-month sample.

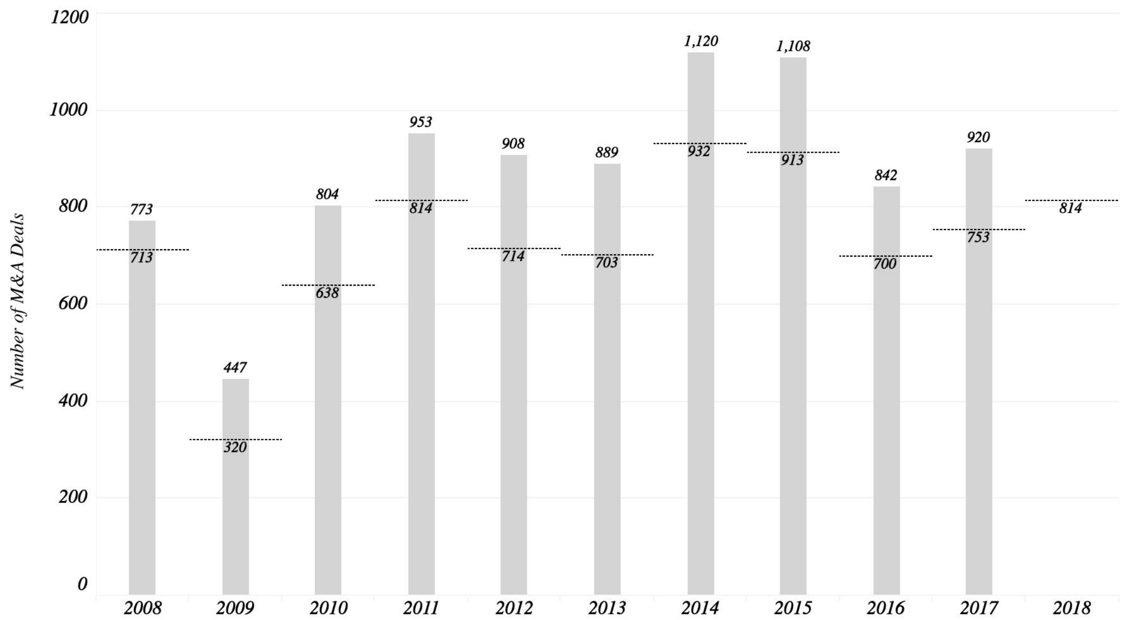

Figure 1: Number of M&A deals of the entire year and the first 10 months of each year.
The bar chart illustrates the total M&A deal numbers of all publicly listed firms in the United States, with a transaction value no smaller than \$100 million, from 2008 to 2018. The dotted line indicates the number of deals of the first 10 months of that year so that the figure of 2018 is comparable. There is a clear surge after the global financial crisis and a potential M&A wave during the period 2011-2015.

M&A deals in the Service industry; Industrial and Electronic Equipment accounts for 28% deals in the Manufacturing industry, followed by Chemical Production (22%) and Health & Other Instrumental Equipment (15%). Nevertheless, firms in such industries are easier to realize economies of scale through mergers or acquisitions.

3.2. Methodology

In this section, I will introduce a set of methods utilized to test the hypotheses. As data of 130 months are collected for the wave sample, there will be residuals if the sample is divided into quintiles using the 24-month wave period. I leave the 10-month period in 2018 so that it will not matter us defining the industries with waves. The quintiles are denoted by Q_1 (2008 – 2009), Q_2 (2010-2011), Q_3 (2012-2013), Q_4 (2014 – 2015), Q_5 (2016-2017). Same groups of quintiles are generated based on the two-digit SIC codes of the industries. Whether there have been waves in an industry depends on the quintiles of that industry only. I try this way to avoid bias on other characters of industry, such as larger or small, vertical or horizontal, high-tech or traditional. [2]

[2] It might be intuitive that larger industries or industries with dynamic characters encounter more restructuring activities. Whether it is true or false does not necessarily affect the results of this study. Even though it is true, this study is dedicated to explaining the drivers of M&A waves in an aggregate level, drivers that should trigger merger waves not only in large or dynamic industries but also in other industries.

3.2.1. Statistical Tests

Starting with H_1 in a single industry, say Finance, to test whether there is a M&A wave, an independent samples t-test is conducted on the quintiles (Q_1 to Q_5), which tests the difference on the means of the quintiles. If the P-value is smaller than 0.05 (two-sided), the null hypothesis is rejected, so that one can conclude that merger deals or tender offers have happened significantly frequent during that period. Also, if the quintile period is known, it can be inferred that there is a M&A wave in the Finance industry for that specific period. Same tests will be then conducted on all other industries and the result table of the wave period of each industry will be demonstrated so that H_1 can be examined.

The results also distinguish the 'with-wave' industries and the 'non-wave' industries — 'non-wave' industries are irrelevant for further tests. I merge the quintiles of each industry and keep the cohorts with only industry-with-wave samples. The I/B/E/S historical financial data of firms are matched with industry-with-wave cohorts using CUSIP code of the bidding firms. The selected independent variables from the I/B/E/S database are Current Liabilities, Current Assets, and Inventories, in order to get the liquidity ratios. The current ratio is defined as

$$r_C = \frac{Current\ Assets}{Current\ Liabilities} \tag{1}$$

and the quick ratio is calculated as

$$r_Q = \frac{Current\ Assets - Inventories}{Current\ Liabilities}. \tag{2}$$

The two liquidity ratios, r_C and r_Q, of every publicly listed firm are calculated for each industry. As the ratios may be affected by the size of the firm, in that larger firms may have better access to financing resources, the value of the firms weights the average current ratio and quick ratio of the whole industry. Then, the weighted average current ratio (R_C) and the weighted average quick ratio (R_Q) are generated for one industry using the liquidity ratios of all firms in that industry. Thus, R_C and R_Q are the proxies, proposed in this study, for capital liquidity of the neoclassical explanations. These two figures are calculated for all industries in the industry-with-wave sample.

The next step is to get the weighted average current and quick ratios of the firms that have announced mergers or tender offers (the bidding firms) within one industry respectively. The weighted average current ratio of the bidding firms is defined as γ_C and the weighted average current ratio of the bidding firms is defined as γ_Q. In the same way, these ratios are calculated for all 'with-wave' industries. A one sample t-test examines the difference of R_C and γ_C (R_Q and γ_Q for quick ratios). The hypotheses are:

$$H_0 : R_C = \gamma_C, \qquad H_a : R_C \neq \gamma_C; \tag{3}$$

$$H_0 : R_Q = \gamma_Q, \qquad H_a : R_Q \neq \gamma_Q. \tag{4}$$

If the null hypothesis is rejected, one can conclude that the average current ratio of the bidding firms is significantly different that of the entire industry, hence the bidding firms have significant differences in liquidity and H_2 is then examined.

Regarding H_3, the weighted average liquidity ratios are derived from the previous results. The current ratios and the quick ratios of the 'with-wave' industries are weighted based on the number of firms of each industry to calculate the average current and quick ratios of the industry-with-wave sample, defined as Γ_C and Γ_Q respectively. Similarly, the average liquidity ratios are also calculated for the 'non-wave' industries, whose notations are Γ_c and Γ_q. Again, independent samples t-tests will be exploited. The hypotheses are:

$$H_0 : \Gamma_C = \Gamma_c, \qquad H_a : \Gamma_C \neq \Gamma_c; \tag{5}$$

$$H_0 : \Gamma_Q = \Gamma_q, \qquad H_a : \Gamma_Q \neq \Gamma_q. \tag{6}$$

If the null hypothesis is rejected, the phenomenon that industries with merger waves have different liquidity will be proved at the market level. The correlations are justified by the probit models

3.2.2. Probit Model

The method of probit models is inspired by Harford (2005) in which he introduced the logit models to estimate the probabilities. For any firm in the market, it has two possible choices — whether to acquire another firm or not. I collect the panel data for the firms in the M&A sample. I further define binary output z as the dependent variable. If a public listed firm makes the decision of merger or acquisition, it is collected in the M&A sample so that $z = 1$. For any other cases in the panel data, binary output z is zero since no mergers or acquisitions is reported.

As neoclassical explanation predicts, the choice of M&A for a firm is affected by the characters of the firm. One may use a regression model to explain this correlation. In this study, such linear model is given by

$$\hat{z} = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + ... + \beta_k x_k + \epsilon, \tag{7}$$

where x_1, x_2, ... ,x_k are the explanatory variables, β_0, β_2, ... ,β_k are coefficients, and ϵ is the error term that is standard normally distributed. While Harford exploited the logit models to compare the significance of factors of both the neoclassical hypothesis and the behavioral hypothesis, I focus on the effect of liquidity ratios and the rate spread. Meanwhile, control variables are also incorporated, such as profitability, asset turnover, capital expenditure, and return on asset, to generate higher explanatory power. Eventually, when $\hat{z} > 0$, the choice will be positive; when $\hat{z} \leq 0$, the choice is no mergers or acquisitions, so that there is

$$Pr(z = 1) = Pr(\hat{z} > 0) = Pr(\epsilon < \sum_{n=0}^{n=k} \beta_n x_{in}) \tag{8}$$

I use function $\Phi(x)$ to describe the distribution of $\hat{z}$. Therefore, the probability of $z = 1$ is defined by the following function:

$$\Phi(Z) = \Phi(\beta_0 + \sum_{n=1}^{n=k} \beta_n X_{in}). \tag{9}$$

In terms of equation (7), the current ratio (r_C) and the quick ratio (r_Q) are the independent variables, because it is predicted that liquidity ratios are the drivers of aggregate M&A waves in recent years. To have better explanatory power, some control variables, predicted by the neoclassical explanations, are also incorporated in the model. The control variables are the proxies for profitability ($P = \frac{Net\ Income}{Sales}$), asset turnover ($T_a = \frac{Sales}{Assets}$), capital expenditure ($E_c$), return on asset ($R = \frac{Net\ Income}{Assets}$), and the rate spread ($r_S$). Hence the full model is given by

$$Z = \beta_0 + \beta_1 r_C + \beta_2 r_Q + \beta_3 P + \beta_4 T_a + \beta_5 E_c + \beta_6 R + \beta_7 r_S. \tag{10}$$

4. Results

4.1. Industry Waves

I start with identifying merger waves in each industry during the sample period. There are quite a few industries that contain only limited numbers of deals such as the Agriculture, Forestry, & Fishing industry (15 recorded deals), and the Public Administration industry (5 recorded deals), so that no waves can be identified. Interestingly, although some industries have small numbers of deals recorded, the deals were triggered within the same period. The Special Trade Contractors industry contains only 28 deals, among which 9 deals were announced between 2012 and 2013. The test result rejects the null hypothesis so that there is a merger wave in the industry during 2012-2013. The industries defined with waves are different from the ones listed by Harford (2005). Hereby the industries are listed in Table 1.

On the contrary, industries with massive deals recorded don't necessarily encounter with a merger wave. For example, the Oil & Gas Extraction industry has 415 merger deals recorded which are equally distributed over the quintiles. Therefore, the null hypothesis cannot be rejected so I cannot define a merger wave. I found 7 other industries with the same results: the Communications industry (355 deals), the Transportation Equipment industry (229 deals), the Fabricated Metal Products industry (106 deals), the Apparel & Accessory Stores industry (105 deals), the Petroleum & Coal Products industry (89 deals), the Pipelines, Except Natural Gas industry (90 deals), and the Hotels industry (77 deals).

Table 1: Industries with merger waves.
The table summaries the industries that have shown significant merger waves examined by the independent samples t-test on the quintile ($Q_1 - Q_5$), at a 95% significant level. The macro industries are characterized by capital letters, where B is for Mining, C for Construction, D for Manufacturing, E for Transportation & Public Utilities, F for Wholesale Trade, G for Retail Trade, H for Finance, Insurance, & Real Estate, and I for Services. Industries whose 2-digit SIC codes are 15, 60, 61, 62 have some numbers of deals in Q_4 and Q_5; thus the waves are counted twice.

Macro	2-Digit SIC & Industry	Wave Period	Period Deals	Total Deals *N*
B.	12 Coal Mining	2010–2011	16	*43*
C.	15 General Building Contractors	2014–2017	24[a]	*49*
	17 Special Trade Contractors	2012–2013	9	*28*
D.	20 Food & Kindred Products	2014–2015	79	*261*
	23 Apparel & Other Textile Products	2014–2015	10	*39*
	26 Paper & Allied Products	2014–2015	20	*77*
	27 Printing & Publishing	2014–2015	20	*61*
	28 Chemical & Allied Products	2014–2015	181	*703*
	30 Rubber & Miscellaneous Plastics	2014–2015	15	*52*

Table 1 *(continued)*

Macro	2-Digit SIC & Industry	Wave Period	Period Deals	Total Deals *N*
	33 Primary Metal Industries	2014–2015	26	*87*
	35 Industrial Machinery & Equipment	2012–2013	97	*423*
	36 Electronic & Electric Equipment	2014–2015	121	*498*
	38 Instruments & Related Products	2010–2011	113	*481*
E.	44 Water Transportation	2012–2013	10	*37*
	45 Transportation by Air	2014–2015	26	*76*
	47 Transportation Services	2014–2015	23	*38*
	49 Electric, Gas & Sanitary Services	2014–2015	94	*351*
F.	51 Wholesale Trade (Non-durable)	2014–2015	34	*125*
G.	53 General Merchandise Stores	2010–2011	21	*72*
	54 Food Stores	2014–2015	14	*37*
	57 Furniture Stores	2010–2011	12	*42*
	58 Eating & Drinking Places	2014–2015	30	*98*
H.	60 Depository Institutions	2014–2017	288[a]	*525*
	61 Non-depository Institutions	2014–2017	56[a]	*113*
	62 Security & Commodity Brokers	2014–2017	106[a]	*241*
	63 Insurance Carriers	2010–2011	77	*321*
	67 Holding & Other Investment Offices	2014–2015	258	*1047*
I.	73 Business Services	2014–2015	232	*1039*
	80 Health Services	2014–2015	40	*152*
	82 Educational Services	2010–2011	16	*31*
	87 Engineering & Management Services	2014–2015	38	*139*

a. Numbers of Deals in both Q_4 and Q_5 are equal and thus are summed.

Table 1 shows the industries with significant M&A waves identified over the 24-month wave period, which compose the ‘industry-with-wave’ sample. The most significant wave period is from 2014 to 2015, which can be examined among almost all macro-industries except for Mining. Finance, Insurance, & Real Estate (FIR) Industry has managed to create its own noteworthy characters. M&A waves are identified in more than one 24-month wave period in many sub-industries (Depository/Non-depository Institution and Security industries) in FIR, for equal numbers of deals are recorded for both 2014-2015 and 2016-2017 wave periods. The t-test results indicate strong confidence level so that both wave periods are significant.

It is easily seen that industry waves cluster over certain periods. Table 2 gives the numbers of industry waves in each 24-month wave period; merger waves were triggered over 22 industries during 2014 – 2015, compared with 2010 – 2011 over 6 industries, 2016 – 2017 over 4 industries, and 2012 – 2013 over 3 industries. Combining the results with Figure 1, one may imply that in the year 2010 and 2011, mergers happened very concentrated on specific industries. Further, based on the neoclassical explanation, it can be inferred that this concentrated wave is due to ‘industry shocks’ that changed the internal or external environment of the firms. Seeing the result of 2014 – 2015, it is rather evident that a new aggregate wave, the 7th M&A wave, has been justified in the most recent decade. The next is to examine the effect of liquidity on these industry waves, and to explain how does liquidity drive this new M&A wave.

Table 2: Number of industries (with merger waves) in each wave period.

Wave Period	*2008–2009*	*2010–2011*	*2012–2013*	*2014–2015*	*2016–2017*
# of Industries	0	6	3	**22**	4

4.2. Liquidity Ratios

I kept the data of the industries that has been shown encountered with merger waves and calculated their liquidity ratios based on the I/B/E/S estimates of historical financial data, matched with CUSIP codes. Then, I conducted statistic tests on the means of the current ratios and the quick ratios of the bidders and the means of the ratios of the entire industry. The results are presented in Table 3. Among all 31 'with-wave' industries, the means are significantly different over 23 industries, although at different significance level. The differences in means of the liquidity ratios of the industries of Apparel & Other Textile Products, Paper & Allied Products, Printing & Publishing, General Merchandise Stores, Food Stores, and Insurance Carriers are not significant. Ratios of some industry categories (47, 60, 61, 62, and 63) cannot be calculated based on the data set and are left omitted. For the rest of the 'with-wave' industries, the average liquidity ratios of the bidders are significantly different from those of all publicly listed firms in that specific industry.

Table 3: Liquidity ratios of each wave industry and its bidding firms. Samples t-test has been conducted in each listed industry, at a 95% significance level, two sided. For industries 47, 60, and 61, liquidity ratios cannot be defined due to lack of financial data, and for industry 62 and 63, bidding firms' inventories data cannot be found.

SIC	R_C (r_C)	R_Q (r_Q)	SIC	R_C (r_C)	R_Q (r_Q)
12	1.814 (1.269)**	1.523 (0.997)**	49	1.337 (1.083)**	1.151 (0.913)**
15	3.156 (1.601)**	2.298 (1.232)**	51	2.358 (1.890)**	1.728 (1.174)**
17	3.353 (1.455)**	3.154 (1.384)**	53	1.708 (1.698)	0.501 (0.540)
20	2.358 (1.942)**	1.573 (1.070)**	54	1.667 (1.528)	0.830 (0.604)
23	2.887 (2.963)	1.810 (1.807)	57	2.148 (2.708)*	1.009 (1.652)*
26	1.919 (1.933)	1.199 (1.222)	58	1.249 (1.119)**	1.445 (1.007)
27	1.529 (1.504)	1.207 (1.222)	60	57.42 (–)	57.39 (–)
28	5.227 (3.326)**	4.939 (2.832)**	61	8.592 (–)	8.542 (–)
30	3.133 (2.136)**	2.125 (1.449)**	62	4.125 (2.039)**	3.875 (–)
33	2.937 (2.739)*	1.791 (1.539)*	63	1.318 (1.378)	omitted
35	6.393 (2.542)**	5.667 (1.892)**	67	7.683 (5.408)**	7.630 (5.374)**
36	3.695 (3.469)*	2.936 (2.805)	73	2.439 (2.221)**	2.396 (2.191)**
38	3.791 (3.141)**	3.090 (2.400)**	80	1.965 (1.658)**	1.873 (1.509)**
44	2.875 (1.949)**	2.799 (1.835)**	82	1.988 (1.853)*	1.944 (1.839)*
45	1.689 (1.381)**	1.496 (1.254)*	87	2.555 (1.644)**	2.446 (1.559)**
47	4.247 (1.422)**	4.228(–)	Observations	*N: 31083*	*n: 6783*

*Significant at 1% level for two sided test; **Significant at 5% level for two sided test.

Surprisingly, the results have indicated some unexpected features of the liquidity ratios. As previous studies have shown, high capital liquidity drives restructuring activities of firms, such as mergers or acquisitions, intensively and extensively over a short period, which will eventually result in an aggregate M&A wave. However, while a new M&A wave has been reported in the last section, Table 3 provides controversial outcomes; The average current ratio of the bidders in one industry is significantly lower than that of the industry level, so does the quick ratio. As a lower current ratio indicates low capital liquidity of the firm, the results reveal an unprecedented phenomenon that firms which choose to merge or takeover on average have lower liquidity than the average liquidity level of the industry. This is contrary to what I have argued in the theoretical framework that the liquidity of individual firms should be high when it announces a merger plan. A lower current ratio indicates either low current assets or high current liabilities, which owners are not willing to see. In this case, managers may use mergers or acquisitions as strategies to improve the financial statement and increase such ratios of the firms in order to meet their obligations to the board, if the transactions are paid by specially designed combinations of equity and debt finance.Thus for most industries, firms conducted mergers have significantly lower liquidity ratios than the average level of that industry.

What can be seen from the results is that firms which have announced such plans have significantly lower liquidity than the industry. However, this does not necessarily mean that the phenomenon is inconsistent with the following tests on the drivers of M&A waves. More importantly, it adds new perspectives on explaining the firm's decision makings, which implies that mergers and acquisitions have been widely applied as a restructuring strategy among the publicly listed companies with relatively lower capital liquidity. If this is true, managers may exploit this feature and analyze its current ratios and quick ratios in order to make strategic plans.

I further calculated the weighted average current ratio of the industries with waves (Γ_C) using the average current ratios of all firms in the 'industry-with-wave' sample to compare with the weighted average current ratio of the industries without merger waves (Γ_c). In a similar vein, the tests are also conducted on the quick ratios. Γ_c is on average 0.1952 lower than Γ_C and the difference is significant at a 5% significance level, whereas Γ_q is 0.0703 lower than Γ_Q but the difference is not statistically significant. (See Table 4.) The difference in current ratios implies that industries with merger waves have higher liquidity than do the industries without merger waves, although their quick ratios may be the same. It is shown that the 'with-wave' industries have higher capital liquidity than the 'non-wave' industries. As a result, the proposal of using liquidity ratios as proxies for capital liquidity is justified. It is consistent with the presumption that aggregate merger waves are triggered by high capital liquidity.

Table 4: Liquidity of the 'With-wave' Industries and the Market.

Wave Industries Γ_C	Non-wave Industries Γ_c	Mean Difference	P-value
3.4008	3.2056	*0.1952*	**0.032**
Wave Industries Γ_Q	Non-wave Industries Γ_q	Mean Difference	P-value
2.3373	2.2670	*0.0703*	0.153

4.3. Probability of Mergers

I used probit models to explain and predict merger waves, in which the merger is a binary output. When a merger is announced by a firm in any year during the period 2008 – 2018, the binary output is equal to 1, and in any other case, the binary output is zero. Table 5 gives the correlation matrix of the independent variables, current ratio and quick ratio, and one of the control variable, rate spread. The current ratio is strongly correlated with the quick ratio, which makes sense because, given equation (1) and (2), the quick ratio is a fraction of the current ratio. To avoid multicollinearity, I only incorporated one of the liquidity ratios in the regression models at a time.

Table 5: Correlation Matrix

	r_C	r_Q	r_S
r_C	1.000		
r_Q	0.979	1.000	
r_S	-0.06	-0.082	1.000

In terms of the correlation between the current ratio and the rate spread, the two variables are negatively correlated, so does the quick ratio and the rate spread. This means that as the rate spread grows, the current ratio or the quick ratio of the firm goes slightly down. However, the figure is very close to zero, so that one may conclude that there are no correlations between either the current ratio and the rate spread, or the quick ratio and the rate spread. Thus, such relations are not necessarily true.

Now it comes to the probit regression. Since Table 3 listed some industries whose quick ratios cannot be calculated, the sample for the probit models is further narrowed. Eventually, I used data from 26 industries to predict the probability of firms announcing a merger or tender offer, over the most recent decade from 2008 to 2018. The liquidity ratios had been taken before the firm announced a merger or tender offer; if a firm announced a merger in 2014, then its financial statement of 2013 is used for getting the ratios. Besides rate spread, other control variables that have been discussed previously are also incorporated in the augmented models. The control variables are the proxies for profitability, asset turnover, capital expenditures, and return on asset. Except for capital expenditure, all the other variables are ratios. Therefore, I took the natural logarithm of the capital expenditure so as to transform the figures into a smaller scale. Taken the natural logarithm also eliminates the outliers of the sample. The confidence levels are set at 5% and 1%.

The regression is run on STATA and the results are illustrated in Table 6. The simple probit model (1) or (2) contains only one independent variable. For model one, the constant is -0.836 and the coefficient is 0.029 which reveals a positive effect of the current ratio on the Z score, $Z = 0.029r_C - 0.836$. For every 0.1 increase in the firm's current ratio, Z increases by 0.0029. If the firm's current ratio is at the average level of the wave industry, 3.40, Z is then calculated as -0.837, and $\Phi(Z) = \Phi(-0.837) \approx 20.05\%$. As the current ratio goes up by 0.1, its probability of conducting a merger is $\Phi(-0.837) \approx 23.25\%$, 3.2% higher than the previous. The Pseudo-R^2 measures the explanatory power of the model, but it is more often used to compare models. Similarly, the Z score of model (2) is $0.031r_Q - 0.824$. The on average, firms with a quick ratio equal to 2.34 have 22.66% of merger or tender offer. If quick ratio increases (from the average level) by 0.1, the probability will be 22.96%, increased by 0.3%. Model (2) has higher Pseudo-R^2 than Model (1). Thus Model (2) has better explanatory power.

The rate spread is the mean difference between the prime loan rate and the Federal Funds rate in a year. Although the former follows the trend of the later to some extent, the spread may vary. Figure 2 shows the figures of both rates over the sample period. Although the loan rate plunged 2009, it remained constant over a long period afterward until 2015, after which surged almost back to the original level in 2018. Meanwhile, the risk-free rate has become volatile after the financial crisis due to the frequently adjusted monetary policies imposed by the Fed. From 2009 to 2015, the Federal Funds rate fluctuated between 0.089% and 0.175% with tiny but intensive adjustments each year. Therefore, the intriguing thing is that the rate spread had been increasing during the 7th M&A wave period when the risk-free rate dropped.

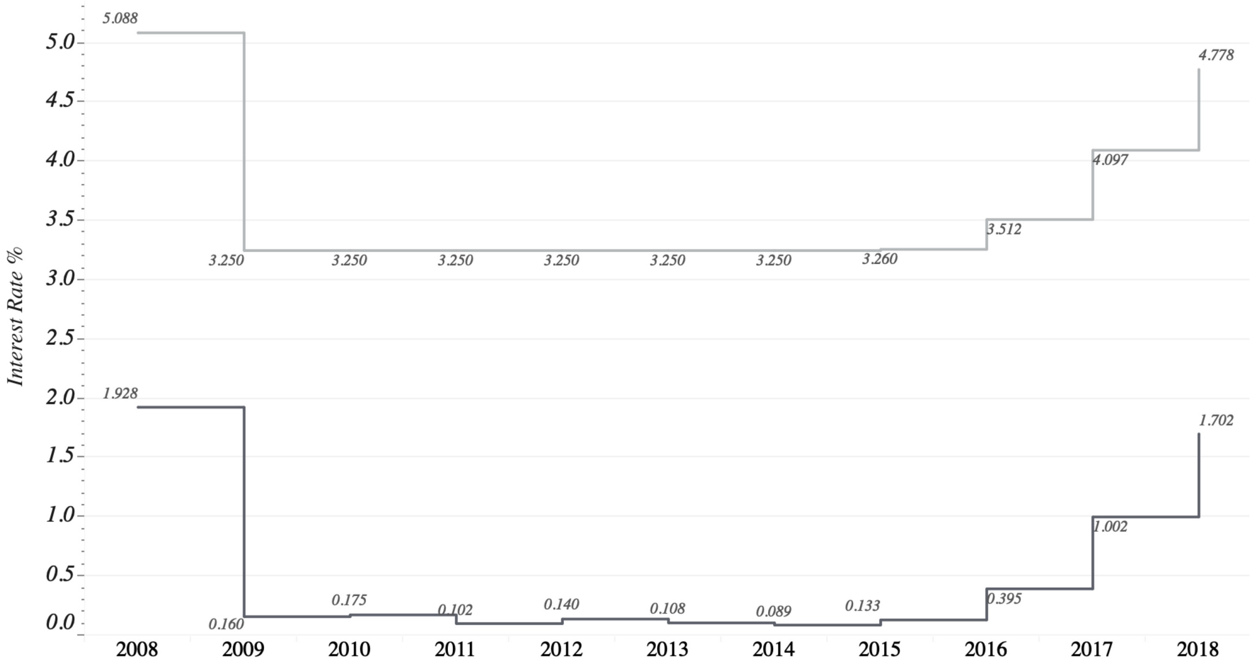

Figure 2: Trends of the prime loan rate and Federal Funds rate. The light gray line demonstrates the changes in company loan rates, while the dark line illustrates those in the Fed interest rates from 2008 to 2018. The rate spread is the distance between the to horizontal bars in between the years. For instance, the rate spread in 2008 is 5.088% – 1.928% = 3.16%.The loan rate remained unchanged during 2009 – 2014 meanwhile the Fed rate dropped by 0.086%.

Model (3) used the rate spread as an independent variable to predict the probability of mergers. Since r_S is measured in years, this model examined the fixed effect of the rate spread on driving a merger. The Z score is $Z = 1.899r_S - 6.17$, so the positive coefficient implies a positive relation between the probability and the rate spread, which is against to the previous studies. I further calculated the predicted probabilities of every year, the maximum is in 2014 when there was 43.25% chance a firm would announce a merger or a tender offer, and the minimum is in 2010 when the chance was 36.69%.

This result has not been reported by previous scholars and the feature is peculiar to the latest M&A wave, the one in 2014 – 2015. Clearly, rate spread will not be a proper proxy for capital liquidity in that the volatile Fed interest rate has created much noise. The microeconomics theory that was introduced early, the 'menu cost' seem to be plausible, yet it is used from the loan issuers' perspective. As the risk-free fluctuating higher or lower, loan issuers will ignore the tiny changes and keep a steady interest rate for companies, which make sense because changing the loan rate incurs costs of accounting and underwriting. Model (4) and Model (5) are used to test omitted variable bias. Compared with the former model, Model (5) has a 0.004 higher Pseudo-R^2 score. Moreover, the coefficient of r_C is no longer significant and the significance level of the coefficient of r_Q has also been compromised. Consequently, adding both of the independent variables does not render the probit model better explanatory power.

Table 6: Predicting merger waves.
Probit models are used to estimate the probability of an industry having a merger wave. I exploited data from 26 industries over the most recent 10 years (2008 – 2018). The table predicts the coefficients and the p-values. The dependent variable is the probability distribution of a merger. Intercept is the constant given by the regression. r_C is the current ratio of a firm, r_Q is the quick ratio of a firm, $ln(CapitalExpenditure)$ is the natural logarithm of the firm's capital expenditure, and ROA is the firm's return on asset. The coefficients are significant at a 99% confidence level if the p-values (p) are smaller than 0.01 or at a 95% confidence level if $0.01 \leq p \leq 0.05$.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Intercept	**−0.836**	**−0.824**	**−6.710**	**−6.894**	**−6.922**	**−6.498**	**−6.502**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Current Ratio r_C	**0.029**			**0.030**	−0.027	**0.099**	
	(0.000)			(0.000)	(0.295)	(0.000)	
Quick Ratio r_Q		**0.031**			**0.058**		**0.108**
		(0.000)			(0.025)		(0.000)
Profitability						0.003	0.004
						(0.487)	(0.377)
Asset Turnover						−0.009	0.009
						(0.601)	(0.606)
$ln(CapitalExpenditure)$						**0.099**	**0.098**
						(0.000)	(0.000)
ROA						−0.024	−0.018
						(0.535)	(0.640)
Rate Spread r_S			**1.899**	**1.939**	**1.955**	**1.633**	**1.641**
			(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Pseudo-R^2	0.040	0.044	0.016	0.057	0.061	0.298	0.312
Observations	*10261*	*10261*	*10261*	*10261*	*10261*	*10156*	*10156*

Finally, besides the rate spread, other control variables are incorporated to generate the full model. Model (6) and Model (7) used either the current ratio or the quick ratio respectively, which together provided with 2 options for the optimal probit model. Evidently, model (7), has higher explanatory power (0.312 compared with 0.298). Nevertheless, the coefficients of either of the models have very rare differences. Test scores also show that the two models cannot be distinguished from one another. Therefore the Z score of both models are given by the Model (6): $Z = -6.498 + 0.099r_C + 0.003P - 0.009T_a + 0.099E_c - 0.024R + 1.633r_S$, or alternatively (7): $Z = -6.502 + 0.108r_Q + 0.004P + 0.009T_a + 0.098E_c - 0.018R + 1.641r_S$.

Coefficients of capital expenditure and rate spread are significantly different from zero and are positive so that the probability of mergers will increase if the two factors increase. Regarding other control variables (profitability, asset turnover and return on assent), the coefficients are not different from zero, and thus one cannot report that there is an effect of any of these factors on changing the probability of mergers. The coefficients of both independent variables of the two model are positive and significantly different from zero. It can be concluded that the higher the liquidity a firm has, the higher the probability it will choose to merge or acquire other firms. Hereby, the empirical meaning of Model (7) can be interpreted as follow: given other factors unchanged and suppose in 2014, a firm's $P = 0.2, T_a = 1.5, E_c = 3, R = 0.3$, and $r_S = 3.16$, if the firm's quick ratio was 1.0 higher than the average level, its probability of conducting a merger will be 3.6% higher than the average.

To sum up, the probit models confirm that liquidity ratios have impacts on the probability of mergers or acquisitions. Since higher liquidity ratios indicate higher capital liquidity, the models show that high capital liquidity drives mergers, which stays in line with the neoclassical explanations. Although the models only predict mergers at the firm level, it helps to explain beyond the neoclassical ideas, for which theory of price stickiness is incorporated. The interpretation is that a firm's managers will react based on the firm's financial reports rather than the figures from the market, which is why rate spread has become ineffective in recent years. When managers see the ratios reported and find out there is higher liquidity, they will choose a restructuring strategy. However, as liquidity ratios are related to the environment of the macroeconomy, it will trigger many firms conducting such strategy simultaneously and thus result in an aggregate merger wave.

The results support the neoclassical explanation, as high liquidity ratios increase the probability of mergers, which is similar to the results reported by previous studies. The new M&A wave is also consistent with explanation, although I found that the industries with massive merger deals and tender offers are slightly different from the industries reported in the last 6 M&A waves, such as the finance industry and the service industry. However, the proxy for capital liquidity, the rate spread, used in previous studies are shown to be improper and are refuted by the price stickiness theory. The empirical results prove that the new measures of capital liquidity, the liquidity ratios proposed by this paper, are plausible alternatives to explain how does liquidity drives the 7th M&A wave that hasn't been discovered before.

5. Discussion & Conclusion

The study contrives to find plausible measures of firms' capital liquidity that can be exploited to explain M&A activities and M&A waves building on the neoclassical hypothesis. The results agreed with the previously reported results of the neoclassical scholars but countered the method of measuring the capital liquidity by showing that previous methods are not suitable given a different and complex market environment.

I first identified the latest M&A wave after the 6th reported one in 2003 – 2007. The 7th M&A wave is then identified to be during 2014 – 2015 when large merger deals or tender offers spread across 22 major industries. The industries that have been examined with merger waves are then compiled as the 'industry-with-wave' sample. I tried to conclude the key features of those firms which have announced mergers compared with the industry. I found intriguingly that the bidding firms in one industry on average have significantly lower liquidity ratios than those of that industry. This phenomenon is founded in 23 out of 31 industries with merger waves. While the reason behind the bidding firms associated with lower liquidity ratios remains unexplained, it shows that liquidity ratios do seem to have correlations between capital liquidity and mergers or acquisitions. Nevertheless, firms with low liquidity may be motivated to make restructuring plans.

The market is then separated into two samples, 'with-wave' industries and 'non-wave' industries. I tested the diffidence in means of the current ratio and quick ratio of the two sample. The test score shows that firms in 'with-wave' industries on average have significantly higher current ratios than the firms in 'non-wave' industries; meanwhile, the same result is also generated for quick ratios but the difference is not statistically significant. Thus, it can be concluded that industries with waves have higher liquidity, which again confirms the neoclassical hypothesis. What's more, liquidity ratios are also justified as plausible measures for capital liquidity.

In previous studies by Harford (2005), the rate spread is used as a proxy for capital liquidity. This paper argues that the frequent adjusted risk-free rates in recent years add much noise to the rate spread. In fact, the 7th M&A wave was triggered when the rate spread reached the peak over the sample period. In the probit models, rate spread also has a positive effect on increasing the probability of mergers, exactly opposite to what Harford argued. The truth is over the wave period, the corporate loan rates remained the same whereas the Federal Funds rate was reduced further and further, resulted in an increased rate spread. I introduced the price stickiness theory to explain this controversy. The loan issuers have ignored the tiny changes of the risk-free rate; they have kept loan interest rates steady in order to avoid more costs. On the other hand, firm managers will also think the changes in the risk-free rate of little importance, as they will not affect the firm's decision-making profoundly. Consequently, the rate spread proxy is no longer valid for the latest wave in 2014 – 2015.

Finally, the probit models are used to estimate the probability. The results indicate that both the current ratio and the quick ratio have positive effects of amplifying the possibility of an underlying merger. Thus, one can conclude that the higher the liquidity a firm has, the higher the probability that it will conduct mergers. The ultimate answer to the research question is that as rate spread lose its power of measuring capital liquidity, liquidity ratios such as the current ratio and the quick ratio can be better alternatives to explain the 7th M&A wave. The interpretations are that within the industries that have relatively higher liquidity, firms with relatively lower are more willing to choose a restructuring activity. The time when firms announce the merger plan or tender offer is when the managers see there is increased capital liquidity from the financial statement. During the period when massive industries possess high capital liquidity, there will be intensive merger deals and tender offers announced so that there will be an aggregate M&A wave.

The study is innovative for it discovered a new M&A wave, using data in the most recent years, which strives for identifying and testing the distinguished features of the 7th M&A wave. It is critical since it challenged the validity of a method that had widely reached consensus among neoclassical scholars, and it is creative in that it not only proposed with a better solution which can address the drawbacks of that method but also incorporated new ideas into to the existing explanations. However, since the M&A wave may be continuing and the data is constrained to publicly listed firms in the United States, the findings are only plausible for the 7th wave specifically. Besides, the control variables listed in the probit models are highly correlated, I suggest researchers to use comprehensive models to avoid potential bias. I also want to encourage scholars to study further the drivers of restructuring strategies given the fact that within an industry, firms choosing to merge have low liquidity. This would be an essential topic for future research.

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