# United States Mergers & Acquisitions Market Dynamics: What drives deal flow in each industry?

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The vast library of mergers and acquisitions research has a long history with no singular focus. Much research has been devoted to the wave-like behavior and drivers of mergers and acquisitions volume at the aggregate level, where many links have been established. The existence of merger waves is well established through the use of autoregressive processes, periodic curve fitting and parameter switching models. However, the causes of merger waves are not well agreed upon. Some authors have provided evidence that merger waves are resultant of clustering M&A activity surges in a small number of industries, and that clustering occurs only in the presence of sufficient capital liquidity at the aggregate level, while others have provided contradicting evidence to that suggestion.

Aggregate M&A activity in the United States has been linked to the capital markets, cyclic macroeconomic variables, deregulation and business expectations. The derived relationships between M&A activity and these variables appears to be highly dependent on the type of data the author uses, as well as the way the data is transformed for econometric purposes, evidenced by inconsistency in the findings among similar research papers. Various authors define M&A activity as the ratio of acquisitions to the total number of firms, while others logarithmically transform M&A volume and take first differences. For some variables, such as the cost of capital, evidence is provided in various papers that could be used to argue just about any hypothesis about the influence of the cost of capital. Some research finds positive relationships, yet other research provides evidence of negative relationships or no significance at all.

The drivers of industry specific M&A activity in the United States have not been researched as comprehensively as aggregate M&A activity, nor have the drivers of M&A activity in those industries been methodically compared. Further, industry specific M&A activity research has seldom been focused on from a forecasting perspective. This paper separates M&A activity in the United States into industry groups and explores the drivers in each from a forecasting perspective, asking the following question: *What drives mergers and acquisitions activity in each industry in the United States, and how do those drivers vary across industries?*

To address the above question, this paper will first survey the universe of relevant literature, which includes research on the existence and causes of merger waves, as well as the drivers of M&A activity. Afterwards, we will introduce the data utilized in this study and present the analysis of the data, which first derives econometric relationships between M&A activity in each industry and various drivers, and then compares the drivers across industries. This paper will end with the key findings and conclusions, as well as suggestions for further research.

## LITERATURE REVIEW

An extensive amount of research pertaining to the relationships between the mergers and acquisitions market and the United States economy has been focused around the existence of merger waves, the causes of merger waves, and the drivers of mergers and acquisitions volume. Evidence of the existence of merger waves in United States has been uncovered in historical data through autoregressive processes (Stughart & Tollison, 1984; Golbe & White, 1988; Barkoulas et al., 2001), fitting a sine curve to historical merger data (Golbe & White, 1993), and parameter switching models such as the Markov regime-switching model (Town, 1992; Resende, 2005; Gärtner & Halbheer, 2009). Merger waves have been hypothesized and shown to be derived from clustering of surges within a small number of industries (Mitchell & Mulherin, 1996; Boone & Mulherin, 2000; Andrade et al., 2001; Harford, 2005), while recent evidence contradicting those theories has also been provided (Gärtner & Halbheer, 2009). Mergers and acquisitions volume has long been tied to the capital markets and business cycle related macroeconomic variables (Nelson, 1959; Beckenstein, 1979; Melicher et al., 1983; Clarke & Ioannidis, 1996), as well as technological innovation (Gort, 1969), Tobin's "q" (Golbe & White, 1988), and more recently tied to business expectations (Carapeto et al., 2010) .

Using autoregressive processes, empirical evidence was first produced against the existence of merger waves, but this theory was quickly challenged. Using United States merger data from 1895 to 1979, Stughart and Tollison were unable to provide evidence that merger activity is not generated simply by a random walk or white-noise process (Stughart & Tollison, 1984). However, they did not actually test a wave hypothesis explicitly; they simply could not reject the null hypothesis that merger activity is governed by a first order autoregressive process, which provoked future researchers to challenge their findings. Golbe and White later uncovered a strong autoregressive dependence in quarterly mergers and acquisitions data, showing empirically that both first and second order autoregressive terms have very strong explaining power, providing evidence against the white-noise theory (Golbe & White, 1988) .

Through successfully fitting a sinusoidal curve to annual data on mergers and acquisitions from 1919 through 1979, Golbe and White provided evidence of the existence of merger waves in the United States. After identifying positive serial correlation in the data, first differences were taken in combination with ordinary least squares estimation to find positive and statistically significant wave amplitude and frequency coefficients in the sinusoidal model. Through this estimation, Golbe and White hypothesized a period of 40 years for the merger waves. The peaks and troughs in the fitted values were qualitatively determined to line up roughly with the peaks and troughs in the actual merger data. Significant explanatory power was provided with their basic sinusoidal model, so they neglected to explore more complex wave forms, leaving that possibility for future research. (Golbe & White, 1993)

Contrary to the findings of Stughart and Tollison and partially in support of merger wave evidence provided by Golbe and White, long-term memory and dependence in merger data were uncovered using higher order autoregressive processes as well as autoregressive fractionally integrated moving average processes (ARFIMA) (Barkoulas et al., 2001). These ARFIMA processes can give rise to waves or stretches of high and low values without regularity or well defined periodicity, supporting the existence of merger waves without requiring the well defined periodicity of a sine wave, which Golbe and White hypothesized. (Barkoulas et al., 2001)

Using a nonlinear, two-state, Markov regime-switching model, Town captured merger wave behavior and fit United States mergers data better than previously used linear ARIMA models using five distinct data sets used in previous merger research. Town claimed that linear models fail to adequately capture the behavior of the merger data and that his nonlinear, Markov regime-switching model is more appropriate. He concluded that mergers and acquisitions alternate between a high mean and variance state and a low mean and variance state, consistent with wave characterization. He also used his model to identify specific merger waves in the historical data and identified nine distinct merger waves between 1898 and 1986. (Town, 1992)

Similarly to Town, others have more recently employed a two-state, Markov regime-switching model to fit merger data in both the United States and

United Kingdom. Resende was able confirm that even for the U.K. mergers data, the model captures behavior well and that persistence and long-term memory appear to be important features (Resende, 2005). Gärtner and Halbheer used quarterly data from 1973 to 2003 to identify merger waves in the U.S. and U.K., but were only able to identify the beginning of a merger wave in the U.S. in 1995, and not the 1980s merger wave that Town uncovered. They conjecture that the reason a 1980s merger wave was not uncovered is because it was dwarfed in the data by the 1990s wave and that the 1980s activity actually looks more normal in comparison. Gärtner and Halbheer also hypothesized that previous econometric misidentifications of the 1980s merger wave could have been due to the use of less refined inference methods (Gärtner & Halbheer, 2009).

Since the existence of merger waves has been well established, researchers have begun focusing more on the causes of merger waves. One of the prominent theories has been that aggregate merger waves are derived from the clustering of mergers and acquisitions activity surges at the industry level (Mitchell & Mulherin, 1996; Boone & Mulherin, 2000; Andrade et al., 2001; Harford, 2005). These M&A activity surges at the industry level are further hypothesized to be a direct result of firms responding rationally to industry shocks in the presence of sufficient capital liquidity (Harford, 2005).

Mitchell and Mulherin took a close look at the causes of the merger wave of the 1980s by separating mergers activity into 51 distinct industries and using basic regression analysis, including dummy variables, to conclude that industry specific shocks such as deregulation, financing innovations, and changes in input costs cause merger waves at the industry level (Mitchell & Mulherin, 1996). Their analysis, unfortunately, restricts merger waves to be two years in duration for each industry without much explanation.

A few years later, similarly, Mulherin and Boone found significant industry clustering during the U.S. merger wave of the 1990s, placing a strong emphasis on the importance of deregulation in industry level mergers and acquisitions activity surging. They also provided empirical evidence discounting the notion that M&A activity in the 1990s was restricted to growth starved industries. (Boone & Mulherin, 2000)

Andrade, Mitchell, and Stafford provided additional evidence in favor of the notion of industry shocks and industry level clustering and took it a step further, claiming that deregulation became a dominant factor in mergers and acquisitions activity in the 1990s, accounting for nearly half of the activity since then. They arrived at this notion by defining a ten-year "deregulation window" around each deregulation event, and find that during the 1980s, roughly 10-15% of total merger activity was represented by industries in a deregulation window, and that in the 1990s, this percentage rose to nearly half of all annual deal volume. Little motivation behind the reason that the deregulation window should be ten years in length is provided, however, and the evidence is not compelling for a well defined causal link between the lengthy deregulation window and mergers volume. Interestingly, by ranking merger activity in each industry over time and correlating across decades, they found no correlation and concluded that industries that undergo mergers and acquisitions activity surges in one decade are no more likely to do so in other decades. Strengthening their point, they showed that the top five industries by merger value in the 1980s differ completely from the top five industries in the 1990s. (Andrade et al., 2001)

A more compelling link has been made between aggregate merger waves and industry level merger activity surges by Harford. Harford claimed that industry shocks cause merger activity surges at the industry level only in the presence of sufficient capital liquidity and that this macro-level capital liquidity causes industry merger waves to cluster in time, even if the industry shocks do not. By employing logit models to predict the start of industry merger waves, Harford found that deregulatory, industry-specific shocks, and capital liquidity have the strongest predictive power. He also discovered that behavioral market oriented variables, such as industry return and standard deviation of returns, only add marginal predictive power. In the aggregate, Harford used the spread between the average interest rate on commercial and industrial loans and the federal funds rate as a proxy for capital liquidity, and industry weighted analogs to his variables at the industry level in his logit model. From his results, Harford noted that a high rate spread reduces aggregate merger activity, behavioral market oriented variables are insignificant, and, shockingly, that deregulation is insignificant in the aggregate model, despite its tremendous importance in the industry level data. He concluded that aggregate merger waves are not propagated by managers attempting to time the market, and that his findings support his hypothesis regarding merger waves and capital liquidity. (Harford, 2005)

Recent empirical findings by Gärtner and Halbheer contradicted the prominent notion that the clustering of mergers and acquisitions activity industry level surges are the cause of waves in aggregate merger activity. Using a two-state, Markov regime-switching model, they identified the 1995 merger wave and then dissected that specific wave at the industry level. By plotting the U.S. industry level merger activity between 1990 through 2003 for the top eleven industries, Gärtner and Halbheer determined qualitatively that industries were not simultaneously hit with the 1995 merger wave, and that the aggregate wave was not the result of a few industry level bursts. After having removed the eleven most active industries in terms of annual merger activity, accounting for 52-66% of the aggregate, the remaining merger activity still resembled a strong wave. (Gärtner & Halbheer, 2009)

Aside from the drivers of mergers and acquisitions activity in the context of merger waves, a tremendous amount of research has been devoted to linking M&A volume to the capital markets, business cycle related macroeconomic variables, and business expectations. Nelson noticed that early mergers and acquisitions surges or waves occurred during a cyclically rising stock market, prompting him to investigate the relationships between aggregate volume and various capital market and macroeconomic conditions. Using de-trended data from 1895 to 1954, Nelson conducted correlation analysis between mergers and acquisitions volume and an industrial stock index's level and trading volume, as well as the index of industrial production. Nelson claimed that aggregate merger activity was more responsive to changes in the capital markets than changes in the level of production, but that it is not clear if the importance of each is causal.

Nelson also analyzed the peaks and troughs in the aggregate mergers and acquisitions activity with those in the industrial stock index level and volume, industrial production level, and business cycle as defined by the National Bureau of Economic Research. During expansions, Nelson noticed that typically there is a peak in stock trading volume first, followed by peaks in merger activity, stock prices, business incorporations, the business cycle, and lastly, industrial production. He noticed during contractions that there normally is a trough in stock prices first, followed by troughs in stock trading, business incorporations, merger activity, industrial production, and the business cycle. Although Nelson's research did not involve typical empirical methods by modern standards or provide solid evidence of any causal relationships, his findings catalyzed future research on the subject of mergers and acquisition activity dynamics. (Nelson, 1959)

One decade later, Gort attempted to unravel the drivers of the merger rate, the ratio of the number of acquisitions to the number of firms, and claimed that the most common economic shocks resulting in mergers activity were rapid changes in technology and movements in securities prices, because they caused a dispersion in valuations. Using data on mergers and acquisitions from 1951 to 1959 classified by industry, Gort performed various econometric analyses, but ultimately restricted the study to the manufacturing related industries. Two proxies were used for technological change: the technical personnel ratio, measured as the number of engineers, chemists and surveyors per 10,000 employees, and the change in labor productivity over time. The concentration ratio, the proportion of industry output contributed by the four largest producers, was taken as a measure of barriers to entry and large firm dominance. Empirically, Gort's econometric models showed that the technical personnel ratio, productivity change, and the concentration ratio were each strongly correlated with merger rates. Lack of stock price indexes that matched his industry level data prevented Gort from properly introducing a stock price variable into the analysis, but he was able to analyze the stock prices of buyers and targets in specific mergers and determined there was no pronounced tendency for buyers to have higher price to earnings ratios than sellers. (Gort, 1969)

In a study of manufacturing and mining merger activity from 1958 to 1975, Beckenstein introduced interest rates on prime commercial paper into his econometric models to capture the effects of the cost of capital on merger activity, along with S&P 500 returns and GNP levels and growth. Through running permutations of his variables, Beckenstein found that the level of the S&P 500 index and the cost of capital proxy variables were significant in the most econometrically sound models, but that the coefficients do not suggest any important role, numerically. Surprisingly, the influence of the cost of capital proxy variables were found to be positive and significant, whereas one might expect the coefficients to be negative since they are directly related to the cost of the merger. Notably, Beckenstein's GNP variable lacked success; it was rarely significant and sometimes had negative coefficients, contrary to intuition. Beckenstein also attempted to implement some log-log models but had difficulty with interpretation and could not achieve a better fit through using them. (Beckenstein, 1979)

In a study between aggregate merger activity, industrial activity, business failures, stock prices and interest rate levels, Melicher, Ledolter, and D'Antonio first used cross correlation techniques between variables to determine proper lag and lead structures for variables and then constructed econometric models. They discovered that mergers and acquisitions activity lags stock market movements and bond yields but leads changes in production, so they restricted their model to include past and present stock prices and bond yields. Using quarterly data covering the 1947 to 1977 time period, their empirical results indicated a weak relationship between merger activity and changes in industrial production, but they had some success with the capital markets variables. They concluded that changes in stock prices and bond yields can be used to forecast future changes in merger activity and that higher stock prices and lower interest rates seem to lead to increased merger activity, partially contradictory to Beckenstein's findings related to the effects of the cost of capital. (Melicher et al., 1983)

In addition to readdressing the cost of capital hypothesis, Golbe and White introduced relative price changes, changes in tax regimes, and Tobin's "q" in their analysis of mergers and acquisition patterns. As a proxy for the cost of capital, they constructed a variable that is a the rate on a Aaa-rated corporate bond less the inflation rate for use in their models, but they were unable to achieve statistical significance using regular OLS estimation. By computing the variance of price changes of the major components of the BLS wholesale price index and the producer price index and aggregating into quarterly values, they created a proxy for changes in economic circumstances, but the variable was insignificant in the model. Tax regime dummy variables were included to account for the 1954, 1963, and 1981 tax regime changes, but they did not add explaining power to the model. Golbe and White also implemented Tobin's q, the ratio of market value to replacement cost, with the expectation that lower q implies a greater bargain, leading to more merger activity. The coefficient on Tobin's q in their regressions was estimated to be positive and significant, which contradicts their hypothesis. Golbe and White found stronger results by running regressions on logarithmically transformed data but still were generally unsuccessful in uncovering the dynamics between fundamental economic factors and mergers and acquisitions activity. (Golbe & White, 1988)

Focusing on the reliability of stock market conditions as predictors of merger activity, Clarke and Ioannidis tested quarterly data on merger activity in the U.K. from 1969 to 1994 for Granger causality. They ran econometric models and Granger causality tests in both directions, testing whether stock market returns Granger cause mergers and acquisitions activity and also testing whether mergers and acquisitions activity Granger causes stock market returns. The hypothesis of "non-causality" from stock market returns to mergers and acquisitions activity was rejected at the 5% level, and they were unable to reject the complementary hypothesis ("non-causality" from mergers activity to stock market returns). From these results, they concluded that stock market returns Granger cause mergers and acquisitions activity in the U.K.. (Clarke & Ioannidis, 1996)

A much more recent study presented by Carapeto, Dallocchio, Faelten, Lanzolla, and Moeller investigates whether business expectations are useful in predicting mergers and acquisitions activity. The authors identified three constituencies of business expectations, including analyst expectations, management expectations, and media expectations. Analyst expectations were measured as the number of buy or sell recommendations in a quarter, the proxy for management expectations was the CEO confidence index, and media expectations were calculated as the number of occurrences of M&A related articles reported by FACTIVA. Using time series and panel data analysis on the first differences of logarithmically transformed U.S. and U.K. mergers data for the 1984 to 2009 time period, they claimed that changes in analyst expectations and management expectations predict and drive mergers and acquisitions activity, but the predictive power is only significant when lagged one quarter. In the U.K. data, their tests unveiled a positive relationship between the number of mergers and acquisitions related articles covered by the media and actual M&A activity. One inherent flaw in their work, however, is that their analyst expectation variable contains unwanted growth because analyst coverage and the number of equity analysts have both been increasing dramatically over time. This results in large increases in the number of buy ratings released over time, but does not necessarily reflect a more optimistic outlook from analysts. A simple scaling by the total number of equity ratings released would have alleviated this issue, but it does not appear that they employed any sort of scaling. The authors acknowledge that it would be interesting for future research to investigate these relationships at the industry level, rather than at the aggregate level. (Carapeto et al., 2010)

In a study of the characteristics leveraged buy-out targets in the United States, it was discovered that more buy-outs occur when risk-free rates are high and the risk premium is low. Using probit models to find the likelihood of a firm going private, the study shows empirically that firms are less likely to LBO if they have high exposure to systematic shocks and higher idiosyncratic risk, which translates directly to high market beta, residual variance, or cash flow volatility. Although leveraged buy-outs have important differences from a typical M&A transaction, extending these ideas into the realm of M&A activity is a small leap. (Haddad et al., 2011)

The vast amount of research related to the behavior of mergers and acquisitions activity and its drivers spans widely; from the existence and causes of merger waves, to macroeconomic and capital market dynamics, as well as the predictive power of business expectations. Much of this research revolves around aggregate mergers and acquisitions volume or a specific set of drivers. Few researchers have broken the issue down to the industry level to unveil distinctions in the dynamics and drivers across industries from a forecasting perspective, which will be the focus of this paper.

## DESCRIPTION OF DATA

Much of the data used in this paper is easily accessible online, with a few key data series sourced from Bloomberg and Capital IQ databases.

### M&A Volume

Mergers and acquisitions volume data was pulled from Capital IQ database for 1976 through 2011. I restricted inclusion to target companies in the United States with transaction value greater than $25mm, and generated industry specific M&A volume data by aggregating individual deals in each industry for every quarter in the time series. Transaction values were recorded at historical, nominal values in US dollars. Overall, M&A volume data for the United States does not appear to be complete in the early years of the data set, but this issue is transient.

### Gross Domestic Product

GDP is seasonally adjusted data from the Bureau of Economic Analysis National Income and Product Accounts Table 1.15.

### Industrial Production

The Index of Industrial Production data was pulled from series G.17 on the Federal Reserve website. IIP is seasonally adjusted and indexed to 2007 = 100.

## S&P Stock Market Indices

Standard & Poor stock market indices were pulled for the aggregate US stock market, as well as for each industry. For the aggregate US stock market, the S&P 500 Index was pulled from Yahoo! Finance historical values, and aggregated into quarterly data via closing prices on the final day of each quarter. The industry specific S&P stock market indices were collected from Bloomberg.

## Stock Market Uncertainty

The 90-day historical volatility in the S&P stock market indices was used as a proxy for uncertainty in the market and was pulled from Bloomberg for each industry, as well as for the S&P 500. A glaring issue with using historical volatility as a proxy for market uncertainty is that it is not forward looking, which is more appropriate for use in forecasting models. Preferably, the proxy variable for uncertainty in the stock market should be the implied volatility, which is backed out of the Black-Scholes model using historical options prices. However, historical option prices on the S&P industry specific indices were not available through any of my resources, so historical volatility will have to suffice.

## Industry Risk Premium

I defined the risk premium for each industry as the market beta of the S&P industry specific index using two years of historical weekly returns from Bloomberg.

Analyst Expectations

I derived the proxy for analyst expectations from equity analyst ratings via Bloomberg. For each industry, the average buy/sell rating on a scale from 1 to 5 for every equity for a given quarter was pulled, which were then averaged to achieve a quarterly equity analyst rating series for each industry. This data is only available as far back as the mid 1990s, where the data begins very sparsely and gradually becomes more complete. Interestingly, the average equity analyst rating never dips below neutral for any quarter, implying that equity analysts tend to be optimistic on average, and that they don't necessarily predict economic downturns. This also implies an analyst coverage bias towards strong performing equities. High levels of the average equity analyst rating for an industry can be interpreted as optimistic analyst expectations of the future, and quarterly increases in the average rating can be interpreted as increasingly optimistic analyst expectations.

Debt Yields

The daily yields on Aaa-rated and Baa-rated corporate debt from Moody's were attained from the Board of Governors of the Federal Reserve System website, as well as the yield on 10-year treasuries from the US Department of Treasure Resource Center. For each series, the daily yields were averaged to form quarterly debt yield data.

## ANALYSIS

To properly determine and assess the drivers of M&A volume and how they vary across general industry groups, I have constructed econometric models at the aggregate level and for each industry to estimate the effects of plausible macroeconomic, capital markets and expectation oriented variables. I will briefly discuss the reasoning behind the inclusion of each variable, provide a prediction of its effect on M&A activity, and then analyze the output of each model. Lastly, I will compare the results across industries.

### Variable Description

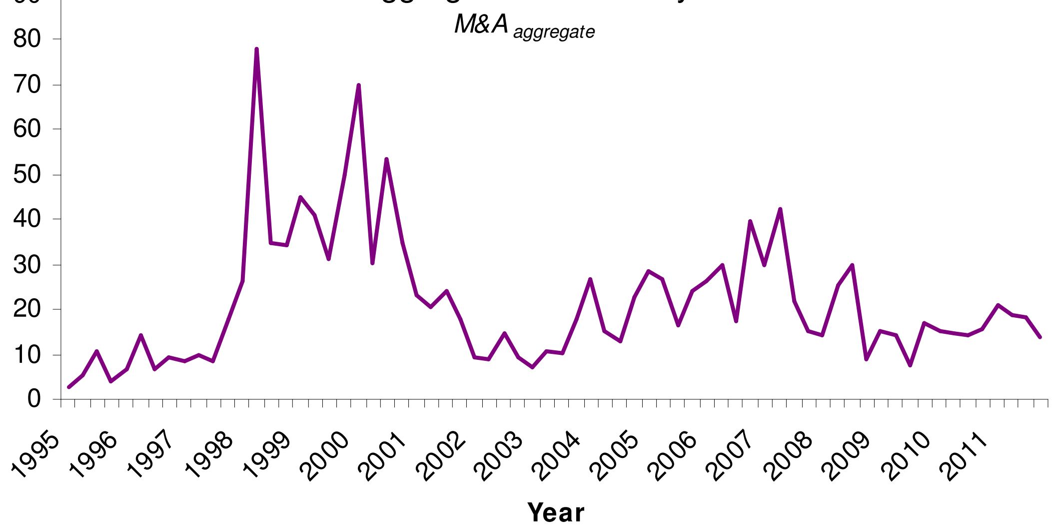
The dependent variable in each model is a time series of the level of M&A activity in industry *i*, which is defined as follows:

(1) $M\&A_{i,t} = M\&A\ Volume_{i,t}\ /\ GDP_t$

This defines M&A activity as the volume of M&A in each industry scaled by the level of GDP, both of which are in nominal terms for consistency. Through scaling by GDP, we partially control for the effects of the business cycle on M&A activity, as well as the time trend, and our definition of M&A activity is relative to GDP. Previous research has uncovered memory in M&A activity through modeling M&A activity with autoregressive processes (Barkoulas et al. 2001). For this reason, the first lag of the dependent variable is included in each model, as well as a second lag in models where it has shown significance.

**Figure 1**

Aggregate M&A Activity

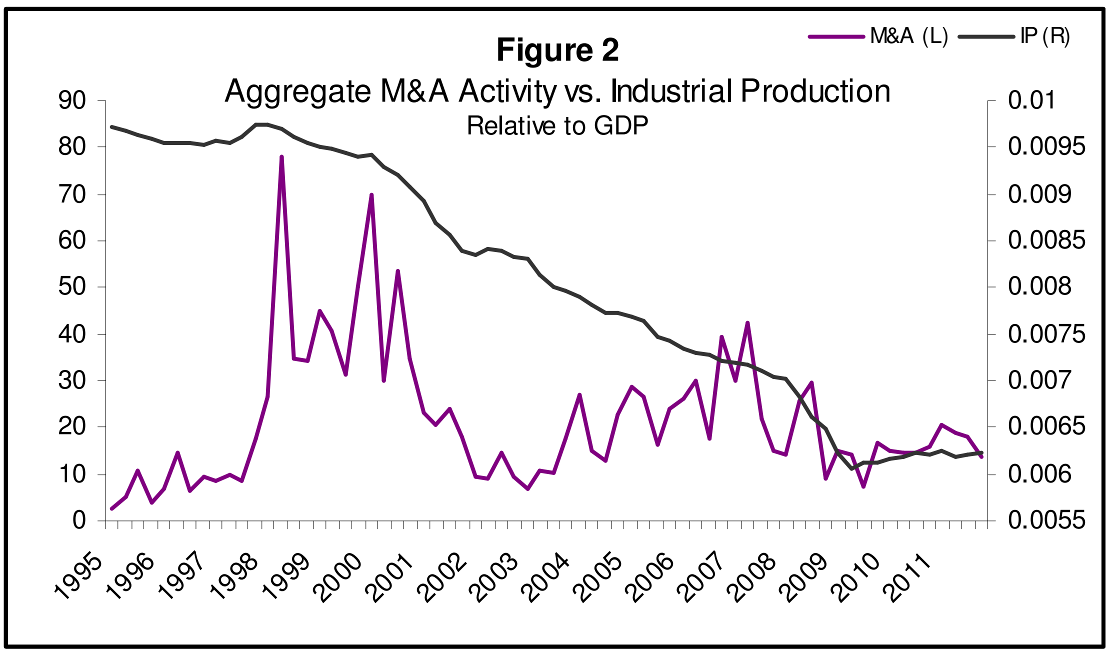



In **Figure 1** above, it is clear that M&A activity tends to spike upwards and then quickly downwards, rather than plateau for some period of time. Because of this, I expect the coefficients on $M\&A_{i,t-1}$ to be negative, promoting unsustainability in high levels of M&A activity.

Past research has established links between industrial production M&A activity in varying degrees of strength and importance, but the majority of the relationships were investigated using aggregate M&A volume (Nelson, 1959; Melicher et al., 1983). I posit that, when broken down at the industry level, industrial production will show varying significance and importance across models, due to industrial production having less relevance in some industries than others. To capture the effects of industrial production on M&A activity, the following variable is defined:

(2) $\quad Industrial\ Prod_t = IIP_t \,/\, GDP_t$

where $IIP_t$ is the index of industrial production. The first lag of *Industrial Prod* will be included in each model. Since high industrial production is an indicator of a healthier economy, I suggest there is a positive relationship between M&A activity and industrial production in general. However, there have been substantiated claims that industrial production peaks after M&A activity peaks (Nelson, 1959), so high industrial production could also mean a large amount of mergers just occurred. For this reason, a negative effect could arise in some industry models as well. Below, **Figure 2** depicts the relationship between aggregate M&A activity and industrial production over the sample period.




An ample amount of research has long linked stock prices to M&A activity, the general notion being that M&A activity lags stock market movements (Nelson, 1959; Melicher et al., 1983), and Granger causality was also established (Clark &

Ioannidis, 1996). The variable used to capture the effects of the stock market with respect to each industry *i* is defined as follows:

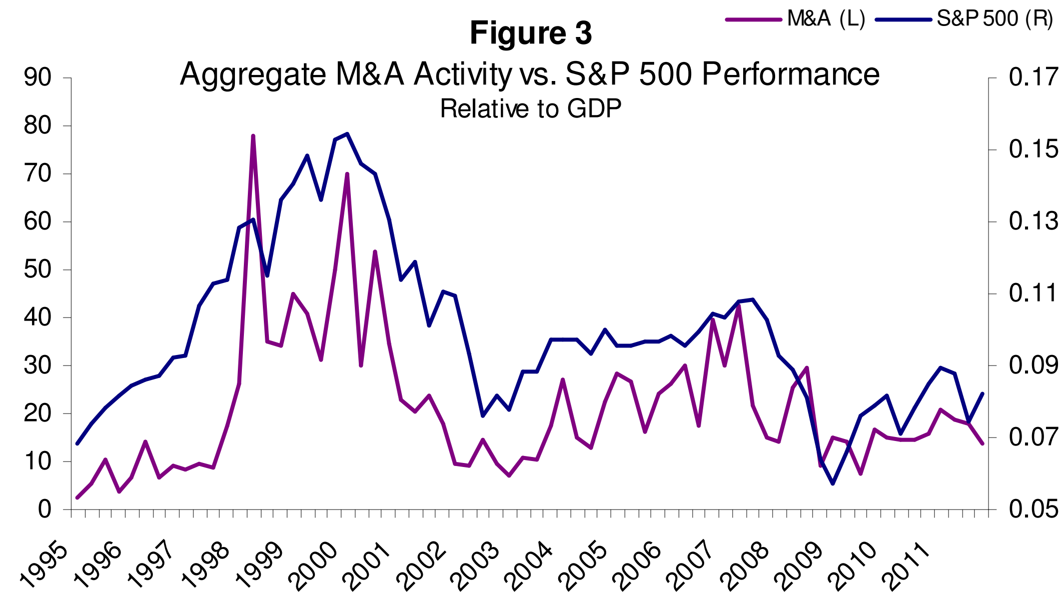
(3) $Stocks_{i,t} = S\&P\ Index_{i,t} / GDP_t$

where $S\&P\ Index_i$ is the S&P Industry *i* market capitalization weighted index level. The first lag of this variable is included in each model, and for the aggregate model the S&P 500 Index is used. Consistent with previous research, I predict the coefficient on $Stocks_{i,t-1}$ will be positive, since M&A activity and the stock market have typically fluctuated together, as seen below in **Figure 3**.

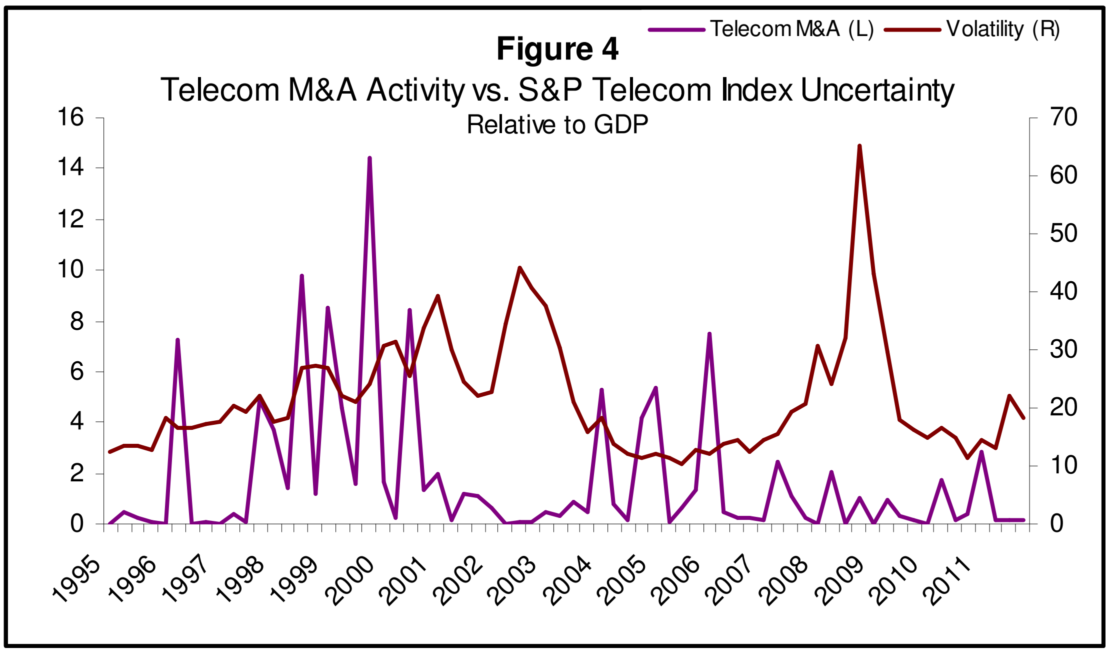
**Figure 3**

Aggregate M&A Activity vs. S&P 500 Performance

Relative to GDP

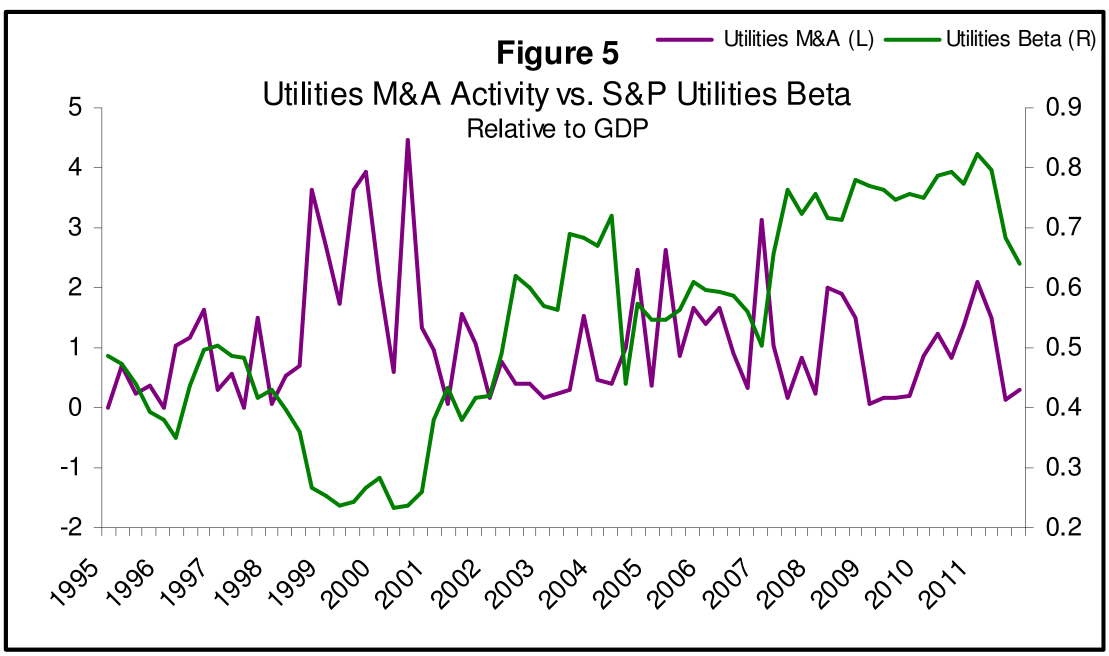



In order to incorporate the effects of stock market uncertainty in the model, I included the 90-day historical volatility of industry *i*'s S&P index returns, named $Uncertainty_{i,t}$. The first lag, $Uncertainty_{i,t-1}$, is included in each model. Uncertainty in the market typically makes ordinary M&A transactions riskier, because the target valuation and pro-forma analysis of the transaction relies heavily on future projections. As uncertainty in the market increases, confidence in those projections, and, ultimately, the valuation itself, decrease. Because of this, I expect the coefficient on $Uncertainty_{i,t-1}$ to be negative for all industries, suggesting that uncertainty during one quarter will result in lower M&A activity in the next. **Figure 4** below plots Telecom M&A activity against S&P Telecom Index volatility, which clearly illustrates the absence of Telecom M&A activity during periods of high uncertainty.



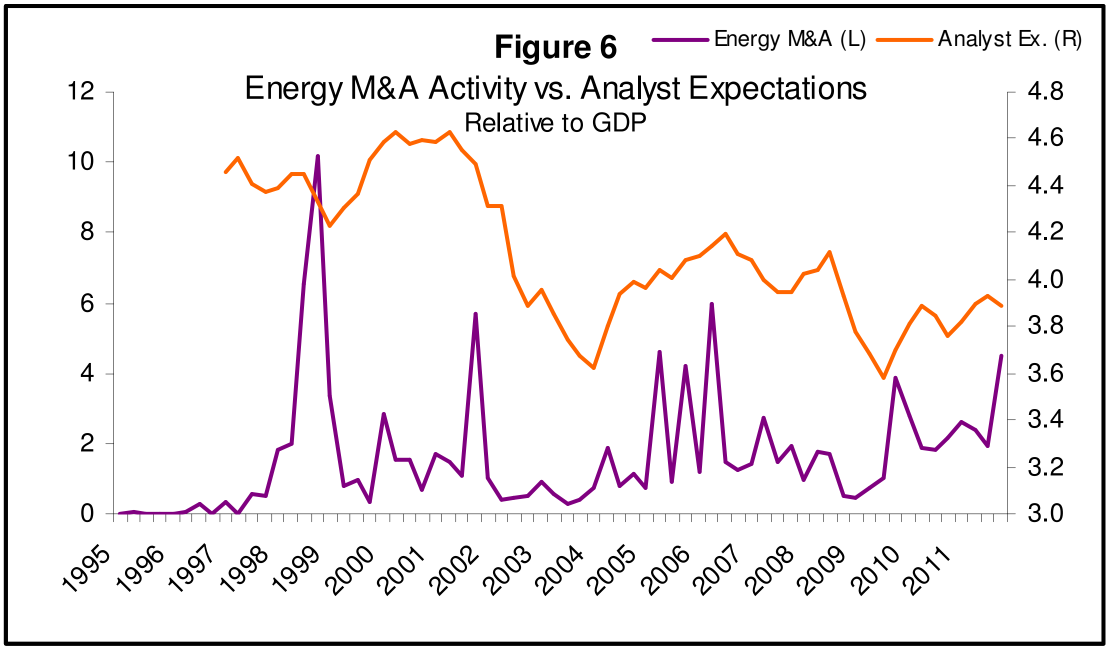

Recently, a link has been established between leveraged buy-out transactions and changes in risk premiums. It was discovered that firms with higher exposure to systematic shocks, or higher market beta, are less likely to be bought out (Haddad et al., 2011). Extending this idea into the realm of M&A transactions in general requires a slight caveat, because LBO transactions are by definition financed with a high level of debt. For this reason, the acquirers prefer the cash flows and performance of the target to be more predictable and less dependent on systematic shocks so that the interest payments on the high level of debt can be made without any default. Since M&A encompasses transactions that are not always funded with debt, the effect of changing risk premiums is likely diluted relative to the effect it has on LBO transaction activity.

In order to incorporate the effects of varying levels of risk premium, I have included $Beta_{i,t-1}$, the first lag of the beta of industry *i*'s S&P Index with respect to the market, in each industry's model. For the reasons highlighted above, I anticipate that the coefficient on $Beta_{i,t-1}$ will be negative. I also will experiment with the first difference of $Beta_{i,t-1}$ in the models to incorporate changes in risk premium, which I also expect to have a negative coefficient with similar reasoning. Below, **Figure 5** depicts the inverse relationship between Utilities M&A activity and the S&P Utilities market beta.



Changes in analyst expectations were also recently tied to M&A activity through the use of equity analyst buy and sell ratings (Carapeto et al., 2010). However, the authors define changes in analyst expectation as the quarterly change in the number of buy ratings released in a quarter for US equities. This is inherently flawed because analyst coverage has been increasing greatly over time, as well as the number of analysts, which creates a major unwanted increase in their proxy for analyst expectations from quarter to quarter.

In order to alleviate this issue, I created a different proxy for analyst expectation that averages all consensus analyst equity ratings on all equities in an industry, named $Analyst_{i,t}$, which varies from 1 (strong sell) to 5 (strong buy) over time. In effect, $Analyst_{i,t}$ represents the average equity analyst rating for industry $i$ at time $t$. The first lag of this proxy for analyst expectation will be included in each industry model. Consistent with previous findings, I expect the coefficient on $Analyst_{i,t-1}$ to be positive, since more optimistic expectations of the market should provoke increased M&A activity. Similarly to the risk premium variable, I will also experiment with the first difference of $Analyst_{i,t-1}$ in order to reveal the effects of changes in analyst expectation, which I also expect to have a positive coefficient for the same reasons. **Figure 6** portrays this positive relationship between Energy M&A activity and equity analyst expectations of the Energy industry.

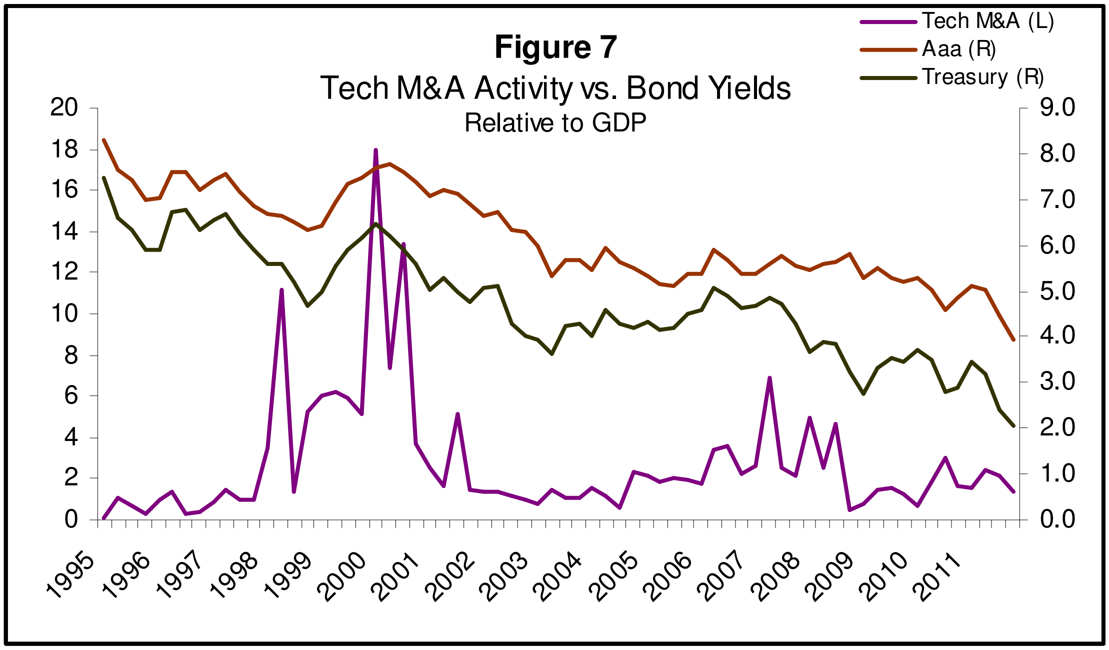


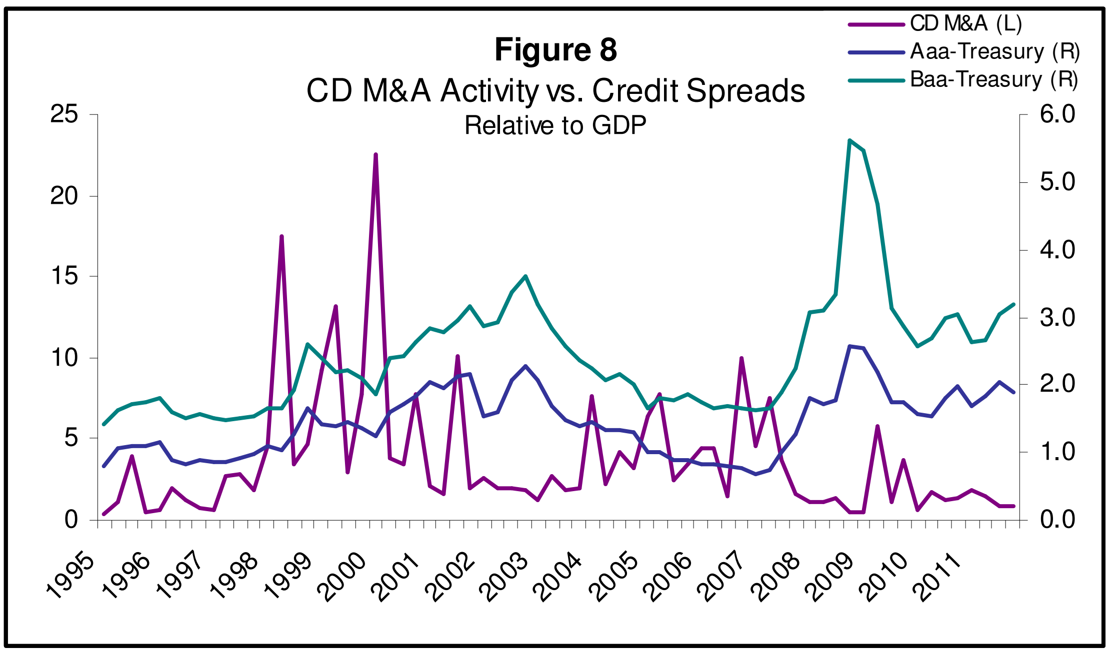

Debt capital markets are a key factor in M&A transactions due to their importance in valuation as well as in financing transactions. The relationship between bond yields and M&A activity has been researched thoroughly in the past and has been identified as a key factor, but with mixed results. A positive relationship was uncovered between the cost of capital and M&A activity in some research (Beckenstein, 1979), others revealed the opposite in later research (Melicher et al., 1983; Harford, 2005), while yet more research found its role to be insignificant (Golbe & White, 1988).

In order to incorporate the effects of the cost of capital on M&A activity, I have introduced several bond yield and credit spread variables into the models for each industry. $AaaBond_{t-1}$ is the first lag of the average yield on a Aaa corporate bond from Moody's, and $Treasury_{t-1}$ is the first lag of the yield on the

10-year treasury note. *Aaa-Treasury*$_{t-1}$ and *Baa-Treasury*$_{t-1}$ represent the first lags of credit spreads for Aaa and Baa corporate bonds from Moody's relative to the yield on the 10-year treasury note.

Since the cost of M&A transactions scale with the bond yields, I expect negative coefficients on each of the bond yield variables. Widening credit spreads signal pessimistic outlooks as well as uncertainty in the corporate domain, so I expect negative coefficients on the credit spread variables as well, consistent with the findings of Harford (Harford, 2005). I will also experiment with the first differences of these variables to see if changes in the cost of capital and credit spreads have a more pronounced impact on M&A activity than levels. I expect the coefficients on the first-differenced variables to also be negative with similar reasoning. **Figure 7** and **Figure 8** below plot Tech M&A activity against bond yields and Consumer Discretionary M&A activity against credit spreads, respectively.




Sample Period

The sample period for the Consumer Discretionary, Energy, Financials, Healthcare, Materials, Technology and Utilities industries, as well as the

Aggregate model, is 1997:Q2 to 2011:Q4. For the Consumer Staples, Industrials and Telecommunications industries, the sample period is 1997:Q3 to 2011:Q4.

Aggregate Model

The full model for aggregate M&A activity is as follows:

(4) $M\&A_{Aggregate,t} = \beta_0 + \beta_1 M\&A_{Aggregate,t-1} + \beta_2 Industrial\ Prod_{t-1} + \beta_3 Stocks_{Aggregate,t-1} + \beta_4 Uncertainty_{Aggregate,t-1} + \beta_5 Analyst_{Aggregate,t-1} + \beta_6 AaaBond_{t-1} + \beta_7 Treasury_{t-1}$

| Aggregate Model | | |
|---|---|---|
| **Variable** | **Coefficient** | **Std. Error** |
| $M\&A_{Aggregate,t-1}$ | -0.04 | (0.27) |
| $Industrial\ Prod_{t-1}$ | 875.75 | (0.33) |
| $Stocks_{Aggregate,t-1}$ | 643.81 *** | (4.16) |
| $Uncertainty_{Aggregate,t-1}$ | 0.33 | (1.50) |
| $Analyst_{Aggregate,t-1}$ | -1.65 | (0.14) |
| $AaaBond_{t-1}$ | -11.53 ** | (2.18) |
| $Treasury_{t-1}$ | 3.97 | (0.91) |
| *Constant* | 3.98 | (0.14) |
| *F Statistic* | *8.76* | |
| *Adjusted* $R^2$ | *0.48* | |
| *N* | *59* | |

* $p<0.1$; ** $p<0.05$; *** $p<0.01$

In the aggregate model, many of the variables are very close to being significant at the 10% level, but do not quite make it. As expected, $Stocks_{Aggregate,t-1}$ has a positive and highly significant coefficient, suggesting that high aggregate stock market values relative to GDP in one quarter predicts high levels of aggregate M&A volume in the next. Also, the coefficient on Aaa-rated corporate bond yields is significant and negative, as expected, suggesting that high, increasing bond yields lead to depressed M&A activity at the aggregate level. This is likely resultant of the increased costs associated with M&A transactions as bond yields increase. Note that the credit spread variables were highly insignificant in the aggregate model and that bond yield levels better described the data.

Consumer Discretionary Model

The full model for Consumer Discretionary M&A activity is as follows:

(5) $M\&A_{CD,t} = \beta_0 + \beta_1 M\&A_{CD,t-1} + \beta_2 Industrial\ Prod_{t-1} + \beta_3 Stocks_{CD,t-1} + \beta_4 D_1(Uncertainty)_{Aggregate,t-1} + \beta_5 D_1(Beta)_{CD,t-1} + \beta_6 Analyst_{CD,t-1} + \beta_7 Aaa\text{-}Treasury_{t-1} + \beta_8 Baa\text{-}Treasury_{t-1}$

| Consumer Discretionary Model | | |
|---|---|---|
| **Variable** | **Coefficient** | **Std. Error** |
| $M\&A_{CD,t-1}$ | -0.38 *** | (3.02) |
| $Industrial\ Prod_{t-1}$ | 988.66 | (1.28) |
| $Stocks_{CD,t-1}$ | 748.24 *** | (4.34) |
| $D_1\ (Uncertainty)_{Aggregate,t-1}$ | -0.13 ** | (2.29) |
| $D_1\ (Beta)_{CD,t-1}$ | 25.40 * | (1.89) |
| $Analyst_{CD,t-1}$ | -1.47 | (0.44) |
| $Aaa\text{-}Treasury_{t-1}$ | -6.18 ** | (2.53) |
| $Baa\text{-}Treasury_{t-1}$ | 3.53 ** | (2.45) |
| *Constant* | -11.60 | (1.43) |
| *F Statistic* | *7.19* | |
| *Adjusted* $R^2$ | *0.46* | |
| *N* | *59* | |

* $p<0.1$; ** $p<0.05$; *** $p<0.01$

In the Consumer Discretionary M&A activity model, high statistical significance was revealed in several variables. The coefficient on the lagged dependent variable is significant and negative as anticipated, suggesting that high levels of M&A activity are typically not sustained; rather, they are relatively short lived. The coefficient on $Stocks_{CD,t-1}$ is positive and significant as expected, signifying a positive relationship between M&A activity in the Consumer Discretionary industry and the market valuation of publicly held Consumer Discretionary companies. The aggregate market uncertainty variable has a negative and significant coefficient, which agrees with the notion that economic uncertainty is detrimental to M&A activity. Interestingly, this model preferred aggregate uncertainty to uncertainty specific to the Consumer Discretionary industry, suggesting that M&A activity in this industry is more influenced by the health of the economy as a whole, rather than a subset of industry specific factors. The significant positive coefficient on the $D_1(Beta)_{CD,t-1}$ suggests that increases in Consumer Discretionary risk premiums with respect to the market in one quarter should lead to an increase in Consumer Discretionary M&A activity in the next, contrary to my hypothesis. It's possible that increasing risk premiums in the Consumer Discretionary industry provokes significant long term investment to fuel growth and promote diversification, and that some firms utilize M&A as a strong source of inorganic growth and stability.

The credit spread variables are both significant but are surprisingly opposing in sign. Historically, the magnitude of the Baa-Treasury spread has been roughly 1.7x that of the Aaa-Treasury spread on average, while the estimated beta coefficient on the Aaa-Treasury spread is roughly -1.8x the coefficient on the Baa-Treasury spread. This suggests that these two credit spread variables are typically correcting and canceling each other in the estimation process, but the overall effect is slightly negative. These results are consistent with the idea that widening credit spreads signals a pessimistic outlook, while directly increasing the cost of financing M&A transactions, therefore prefacing decreased M&A activity.

<u>Consumer Staples Model</u>

The full model for Consumer Staples M&A activity is as follows:

(6) $$M\&A_{CS,t} = \beta_0 + \beta_1 M\&A_{CS,t-1} + \beta_2 Industrial\ Prod_{t-1} + \beta_3 Stocks_{Aggregate,t-1} + \beta_4 D_1(Uncertainty)_{CS,t-1} + \beta_5 D_1(Beta)_{CD,t-1} + \beta_6 D_1(Analyst)_{CS,t-1} + \beta_7 AaaBond_{t-1} + \beta_8 D_1(Treasury)_{t-1}$$

| Consumer Staples Model | | |
|---|---|---|
| **Variable** | **Coefficient** | **Std. Error** |
| $M\&A_{CS,t-1}$ | 0.02 | (0.14) |
| $Industrial\ Prod_{t-1}$ | -706.62 ** | (2.24) |
| $Stocks_{Aggregate,t-1}$ | 48.62 *** | (3.66) |
| $D_1(Uncertainty)_{CS,t-1}$ | -0.02 | (0.66) |
| $D_1(Beta)_{CS,t-1}$ | 7.48 ** | (2.25) |
| $D_1(Analyst)_{CS,t-1}$ | 1.47 | (0.62) |
| $AaaBond_{t-1}$ | 0.31 | (0.80) |
| $D_1(Treasury)_{t-1}$ | -0.92 * | (1.79) |
| *Constant* | -0.92 * | (1.79) |
| *F Statistic* | *2.56* | |
| *Adjusted* $R^2$ | *0.18* | |
| *N* | *58* | |

* $p$<0.1; ** $p$<0.05; *** $p$<0.01

The Consumer Staples M&A activity model reveals statistical significance in the industrial production variable, with a negative coefficient. Contrary to the Consumer Discretionary model results, this model showed much more significance in aggregate stock market health rather than specifically the Consumer Staples industry. This suggests that the Consumer Staples M&A market is more dependent on the health of the stock market as a whole, though market uncertainty did not appear to be a salient factor. Consistent with the findings of the Consumer Discretionary model, the effect of changes in risk premiums is significant and positive. Significance was also found in a negative coefficient on changes in treasury yields, consistent with the notion that higher treasury rates leads to greater discounting of future cash flows, and thus lower anticipated benefit from an M&A transaction. Note that the credit spread variables were highly insignificant in the model and were omitted in favor of the bond yield variables.

Energy Model

The full model for Energy M&A activity is as follows:

$$(7) \quad M\&A_{Energy,t} = \beta_0 + \beta_1 M\&A_{Energy,t-1} + \beta_2 Industrial\ Prod_{t-1} + \beta_3 Stocks_{Aggregate,t-1} + \beta_4 Uncertainty_{Energy,t-1} + \beta_5 Beta_{Energy,t-1} + \beta_6 Analyst_{Energy,t-1} + \beta_7 AaaBond_{t-1} + \beta_8 Treasury_{t-1}$$

| Energy Model | | |
|---|---|---|
| Variable | Coefficient | Std. Error |
| $M\&A_{Energy,t-1}$ | 0.11 | (0.77) |
| $Industrial\ Prod_{t-1}$ | 566.75 | (1.34) |
| $Stocks_{Aggregate,t-1}$ | 5.48 | (0.30) |
| $Uncertainty_{Energy,t-1}$ | -0.01 | (0.59) |
| $Beta_{Energy,t-1}$ | 1.92 | (1.51) |
| $Analyst_{Energy,t-1}$ | 4.01 ** | (2.39) |
| $AaaBond_{t-1}$ | -1.37 * | (1.74) |
| $Treasury_{t-1}$ | -0.49 | (0.77) |
| *Constant* | -0.49 | (0.77) |
| *F Statistic* | *2.23* | |
| *Adjusted $R^2$* | *0.14* | |
| *N* | *59* | |

* $p<0.1$; ** $p<0.05$; *** $p<0.01$

This is the first model to reveal significance in analyst expectations. The positive and significant coefficient on $Analyst_{Energy,t-1}$ suggests that a quarter of high analyst expectations prefaces a quarter of increased Energy M&A activity, consistent with my expectation. Significance was also achieved in the Aaa corporate bond yield variable, and the negative coefficient also agrees with my hypothesis.

The fit and overall variable significance for the Energy M&A activity model is less than ideal. It is possible that other factors such as deregulation have played a large role in recent M&A activity for the Energy industry, or perhaps it has more to do with changes in input prices and technology.

<u>Financials Model</u>

The full model for Financials M&A activity is as follows:

(8) $M\&A_{Financials,t} = \beta_0 + \beta_1 M\&A_{Financials,t-1} + \beta_2 Industrial\ Prod_{t-1} + \beta_3 Stocks_{Financials,t-1} + \beta_4 Beta_{Financials,t-1} + \beta_5 Analyst_{Financials,t-1} + \beta_6 AaaBond_{t-1} + \beta_7 D_1(Treasury)_{t-1}$

| Financials Model | | |
|---|---|---|
| **Variable** | **Coefficient** | **Std. Error** |
| $M\&A_{Financials,t-1}$ | 0.04 | (0.28) |
| $Industrial\ Prod_{t-1}$ | 1253.64 | (0.65) |
| $Stocks_{Financials,t-1}$ | 329.36 * | (1.92) |
| $Beta_{Financials,t-1}$ | 5.98 | (1.57) |
| $Analyst_{Financials,t-1}$ | -0.32 | (0.07) |
| $AaaBond_{t-1}$ | -2.24 | (1.40) |
| $D_1(Treasury)_{t-1}$ | -2.25 | (1.23) |
| *Constant* | -7.31 | (0.86) |
| *F Statistic* | *1.56* | |
| *Adjusted* $R^2$ | *0.06* | |
| *N* | *59* | |

* $p<0.1$; ** $p<0.05$; *** $p<0.01$

The Financials M&A activity model also exhibits very poor variable significance, as well as poor fit. Similarly to the Energy industry, this may suggest that the Financial industry M&A market is more motivated by factors such as changes in regulation, and less dependent on valuation drivers and expectations. There is significance in the coefficient on the $Beta_{Financials,t-1}$ variable however, which suggests that periods of high equities prices in the financial industry relative to GDP leads to an increase in Financials M&A activity. Neither the bond yield variables nor the credit spread variables were able to achieve any reasonable level of significance.

Healthcare Model

The full model for Healthcare M&A activity is as follows:

(9) $M\&A_{Healthcare,t} = \beta_0 + \beta_1 M\&A_{Healthcare,t-1} + \beta_2 Industrial\ Prod_{t-1} + \beta_3 Stocks_{Aggregate,t-1} + \beta_4 D_1(Beta)_{Healthcare,t-1} + \beta_5 Analyst_{Healthcare,t-1} + \beta_6 D_1(Aaa\text{-}Treasury)_{t-1} + \beta_7 D_1(Baa\text{-}Treasury)_{t-1}$

| Healthcare Model | | |
|---|---|---|
| **Variable** | **Coefficient** | **Std. Error** |
| $M\&A_{Healthcare,t-1}$ | 0.06 | (0.43) |
| $Industrial\ Prod_{t-1}$ | -876.34 * | (1.78) |
| $Stocks_{Aggregate,t-1}$ | 65.85 *** | (2.68) |
| $D_1\ (Beta)_{Healthcare,t-1}$ | 11.07 ** | (2.06) |
| $Analyst_{Healthcare,t-1}$ | -0.90 | (0.53) |
| $D_1\ (Aaa\text{-}Treasury)_{t-1}$ | -2.83 | (1.15) |
| $D_1\ (Baa\text{-}Treasury)_{t-1}$ | 2.84 ** | (2.20) |
| *Constant* | 6.40 | (1.23) |
| *F Statistic* | *2.56* | |
| *Adjusted $R^2$* | *0.16* | |
| *N* | *59* | |

* $p$<0.1; ** $p$<0.05; *** $p$<0.01

The Healthcare M&A activity model exhibits reasonable statistical significance in some variables. Similarly to the Consumer Staples model, there is a negative and significant coefficient on the industrial production variable, and the Healthcare M&A activity model also reveals much more significance in the health of the aggregate stock market rather than equities specific to the Healthcare industry  There is a positive and significant coefficient on the variable for changes in risk premiums with respect to the market, consistent with the findings in the Consumer Discretionary and Consumer Staples models. The Baa-Treasury credit spread variable coefficient is positive and significant, contrary to my expectation, suggesting that widening credit spreads actually lead to increased Healthcare M&A activity.

Despite showing reasonable variable significance, the Healthcare M&A activity model demonstrates poor fit. Healthcare is likely another industry that has an M&A market strongly motivated by changes in regulation. It is also possible that Healthcare M&A activity is provoked by some factors unique to the industry, such as acquiring patents on new drugs, which are largely independent of broad economic and capital markets factors.

Industrials Model

The full model for Industrials M&A activity is as follows:

(10) $M\&A_{Industrials,t} = \beta_0 + \beta_1 M\&A_{Industrials,t-1} + \beta_2 Industrial\ Prod_{t-1} + \beta_3 Stocks_{Aggregate,t-1} + \beta_4 D_1(Uncertainty)_{Industrials,t-1} + \beta_5 Beta_{Industrials,t-1} + \beta_6 D_1(Analyst)_{Industrials,t-1} + \beta_7 D_1(Aaa\text{-}Treasury)_{t-1} + \beta_8 D_1(Baa\text{-}Treasury)_{t-1}$

| Industrials Model | | |
|---|---|---|
| Variable | Coefficient | Std. Error |
| $M\&A_{Industrials,t-1}$ | -0.11 | (0.84) |
| $Industrial\ Prod_{t-1}$ | -436.22 * | (1.74) |
| $Stocks_{Aggregate,t-1}$ | 60.92 *** | (4.27) |
| $D_1\ (Uncertainty)_{Industrials,t-1}$ | -0.02 | (0.70) |
| $Beta_{Industrials,t-1}$ | -2.20 | (1.26) |
| $D_1\ (Analyst)_{Industrials,t-1}$ | -2.43 | (0.91) |
| $D_1\ (Aaa\text{-}Treasury)_{t-1}$ | 2.22 * | (1.72) |
| $D_1\ (Baa\text{-}Treasury)_{t-1}$ | -1.11 | (1.41) |
| *Constant* | 1.70 | (0.62) |
| *F Statistic* | *6.29* | |
| *Adjusted $R^2$* | *0.43* | |
| *N* | *58* | |

* $p<0.1$; ** $p<0.05$; *** $p<0.01$

The Industrials M&A activity model has great fit relative to most other models, but significance is lacking on many of the variables. Also, note that $Stocks_{Aggregate,t-1}$ has exceptionally high significance, much more than the stock market variable restricted to Industrials equities, suggesting that Industrials M&A activity might also be driven more by the health of the aggregate market than its own. Notably, industrial production is significant in the model of Industrial M&A activity with a negative coefficient, contradicting my expectation. It is possible that Industrial M&A activity actually leads industrial production, rather than lagging it. Consistent with the Healthcare M&A activity model, there is a positive and significant coefficient on a first differenced credit spread variable, but here it is the Aaa-Treasury spread. This once again suggests that a widening credit spread actually leads to increases in M&A activity in the Industrials industry.

Materials Model

The full model for Materials M&A activity is as follows:

(11) $M\&A_{Materials,t} = \beta_0 + \beta_1 M\&A_{Materials,t-1} + \beta_2 Industrial\ Prod_{t-1} + \beta_3 Stocks_{Aggregate,t-1} + \beta_4 Uncertainty_{Materials,t-1} + \beta_5 D_1(Beta)_{Materials,t-1} + \beta_6 Analyst_{Materials,t-1} + \beta_7 Aaa\text{-}Treasury_{t-1} + \beta_8 Baa\text{-}Treasury_{t-1}$

| Materials Model | | |
|---|---|---|
| **Variable** | **Coefficient** | **Std. Error** |
| $M\&A_{Materials,t-1}$ | -0.16 | (1.26) |
| $Industrial\ Prod_{t-1}$ | -458.71 *** | (3.54) |
| $Stocks_{Aggregate,t-1}$ | 38.24 *** | (4.74) |
| $Uncertainty_{Materials,t-1}$ | 0.01 | (0.37) |
| $D_1\ (Beta)_{Materials,t-1}$ | -2.66 * | (2.01) |
| $Analyst_{Materials,t-1}$ | -0.31 | (0.60) |
| $Aaa\text{-}Treasury_{t-1}$ | -1.10 ** | (2.30) |
| $Baa\text{-}Treasury_{t-1}$ | 0.35 | (0.87) |
| Constant | 2.85 | (1.52) |
| *F Statistic* | *6.43* | |
| *Adjusted $R^2$* | *0.43* | |
| *N* | *59* | |

* $p$<0.1; ** $p$<0.05; *** $p$<0.01

The Materials industry M&A activity model produces strong variable significance in a few variables. With respect to the aggregate stock market health and industrial production variables, the results align with many of the previous models. The coefficient on the $D_1(Beta)_{Materials,t-1}$ variable is negative and significant, suggesting that the materials industry M&A activity decreases after periods of increasing risk premiums with respect to the market. This is contrary to the findings in previous models, where the coefficient was positive and significant. The coefficient on the Aaa-Treasury credit spread variable is negative and significant, consistent with expectations and a few of the previous models.

Technology Model

The full model for Technology M&A activity is as follows:

(12) $M\&A_{Tech,t} = \beta_0 + \beta_1 M\&A_{Tech,t-1} + \beta_2 Industrial\ Prod_{t-1} + \beta_3 Stocks_{Tech,t-1} + \beta_4 Uncertainty_{Aggregate,t-1} + \beta_5 Beta_{Tech,t-1} + \beta_6 Analyst_{Tech,t-1} + \beta_7 Aaa\text{-}Treasury_{t-1}$

| Technology Model | | |
|---|---|---|
| **Variable** | **Coefficient** | **Std. Error** |
| $M\&A_{Tech,t-1}$ | -0.44 *** | (3.42) |
| $Industrial\ Prod_{t-1}$ | -50.71 | (0.12) |
| $Stocks_{Tech,t-1}$ | 222.60 *** | (7.05) |
| $Uncertainty_{Aggregate,t-1}$ | 0.06 | (1.30) |
| $Beta_{Tech,t-1}$ | -2.61 | (0.77) |
| $Analyst_{Tech,t-1}$ | -1.83 | (0.98) |
| $Aaa\text{-}Treasury_{t-1}$ | -1.99 ** | (2.33) |
| Constant | 9.73 | (1.27) |
| *F Statistic* | *14.01* | |
| *Adjusted* $R^2$ | *0.61* | |
| *N* | *59* | |

* $p<0.1$; ** $p<0.05$; *** $p<0.01$

The Technology M&A activity model has fantastic fit relative to most other models. There is high significance in the lagged dependent variable as well as the Technology industry stock market variable, suggesting once again that periods of strong M&A activity are typically unsustainable in the Technology sector and that M&A activity has a strong positive relationship with Technology stock prices. The remaining significance is found in the Aaa-Treasury credit spread, which has a negative coefficient, as expected.

Telecom Model

The full model for Telecom M&A activity is as follows:

(13) $M\&A_{Telecom,t} = \beta_0 + \beta_1 M\&A_{Telecom,t-1} + \beta_2 M\&A_{Telecom,t-2} + \beta_3 Industrial\ Prod_{t-1} + \beta_4 Stocks_{Aggregate,t-1} + \beta_5 Uncertainty_{Telecom,t-1} + \beta_6 D_1(Beta)_{Telecom,t-1} + \beta_7 D_1(Analyst)_{Telecom,t-1} + \beta_8 D_1(Aaa\text{-}Treasury)_{t-1} + \beta_9 Baa\text{-}Treasury_{t-1}$

| Telecom Model | | |
|---|---|---|
| **Variable** | **Coefficient** | **Std. Error** |
| $M\&A_{Telecom,t-1}$ | -0.30 ** | (2.43) |
| $M\&A_{Telecom,t-2}$ | -0.22 * | (1.70) |
| $Industrial\ Prod_{t-1}$ | 1485.38 *** | (2.82) |
| $Stocks_{Aggregate,t-1}$ | 57.08 ** | (2.06) |
| $Uncertainty_{Telecom,t-1}$ | -0.20 *** | (2.88) |
| $D_1(Beta)_{Telecom,t-1}$ | -1.07 | (0.25) |
| $D_1(Analyst)_{Telecom,t-1}$ | 6.23 *** | (3.49) |
| $D_1(Aaa\text{-}Treasury)_{t-1}$ | 3.38 ** | (2.40) |
| $Baa\text{-}Treasury_{t-1}$ | 2.22 *** | (2.76) |
| Constant | -15.88 *** | (4.17) |
| *F Statistic* | *5.75* | |
| *Adjusted* $R^2$ | *0.43* | |
| *N* | *58* | |

* $p<0.1$; ** $p<0.05$; *** $p<0.01$

The Telecommunications M&A activity model shows tremendous statistical significance across many variables. Both the first and second lags of the dependent variable are significant and negative, as expected. Contrary to all other models, the industrial production variable has a positive and highly significant coefficient. As expected, the variable for uncertainty in the Telecom industry has a negative and very significant coefficient. The positive coefficient on $D_1(Analyst)_{Telecom,t-1}$ suggests that M&A activity in the Telecom industry is highly driven by changes in analyst expectations, with M&A activity increasing after analyst expectations increase.

The positive and significant coefficient on the first difference of the Aaa-Treasury credit spread again suggests that widening credit spreads lead to increases in M&A activity in the Telecom industry, among other industries. Interestingly, there is also a positive and significant coefficient on the level of the Baa-Treasury credit spread. Along with the positive coefficient on the analyst expectation variable, these results suggest that Telecom M&A activity tends to boom when default risk in corporations is high relative to the government, with analysts revising expectations of the future upward. It is possible that this is an ideal time for Telecom corporations to make large capital investments, potentially in the form of an M&A transaction.

Utilities Model

The full model for Utilities M&A activity is as follows:

(14) $M\&A_{Utilities,t} = \beta_0 + \beta_1 M\&A_{Utilities,t-1} + \beta_2 Industrial\ Prod_{t-1} + \beta_3 Stocks_{Aggregate,t-1} + \beta_4 Uncertainty_{Utilities,t-1} + \beta_5 Beta_{Utilities,t-1} + \beta_6 Analyst_{Utilities,t-1} + \beta_7 D_1(Aaa\text{-}Treasury)_{t-1}$

| Utilities Model | | | |
|---|---|---|---|
| Variable | Coefficient | | Std. Error |
| *M&A* $_{Utilities,t-1}$ | -0.13 | | (0.94) |
| *Industrial Prod* $_{t-1}$ | -645.32 | *** | (2.88) |
| *Stocks* $_{Aggregate,t-1}$ | 14.88 | | (1.27) |
| *Uncertainty* $_{Utilities,t-1}$ | -0.04 | ** | (2.11) |
| *Beta* $_{Utilities,t-1}$ | -5.32 | *** | (2.82) |
| *Analyst* $_{Utilities,t-1}$ | -0.93 | | (1.29) |
| $D_1$ *(Aaa-Treasury)* $_{t-1}$ | 1.37 | ** | (2.29) |
| Constant | 11.86 | *** | (2.90) |
| *F Statistic* | *4.39* | | |
| *Adjusted* $R^2$ | *0.29* | | |
| *N* | *59* | | |

* $p$<0.1; ** $p$<0.05; *** $p$<0.01

This model shows great significance in many variables. The industrial production variable shows very strong significance and is negative, consistent with most previous models. Utilities industry uncertainty is also significant and negative, suggesting that high uncertainty in the market in one quarter is detrimental to M&A activity in the next, as expected. The Utilities risk premium variable is also significant and negative, which suggests increases in risk premiums in the Utilities industry with respect to the market leads to a decrease in M&A activity in the Utilities industry. Similarly to some of the previous findings, it appears that the Utilities industry M&A activity also increases as the spread between corporate bond yields and treasuries widens.

## M&A Activity Drivers Across Industries: Similarities and Differences

For simple comparative purposes, the estimated effects of the proposed drivers of M&A activity in each industry have been aggregated and organized in

**Figure 9**, located in **Appendix A**. As seen in **Figure 9**, the drivers across each industry tend to vary in both salience and effect. I will now go through each driver individually and discuss similarities and differences across industry groups.

<u>Past M&A Activity</u>

Using lags of the dependent variable for each industry showed varying significance across models, but the estimated effect was consistently negative. The negative impact of past M&A activity aligns with my expectation and agrees with the notion that M&A activity has a short-term bursting behavior. It is possible that this past dependence is due to chain reaction merger activity, where the merging of two firms provokes competitors to quickly seek out their M&A opportunities to remain competitive themselves. This would result in short term bursts in M&A activity in an industry, given the sufficiency of other factors such as capital liquidity and economic optimism.

The industries in which past M&A activity proved to be most significant were the Consumer Discretionary, Technology and Telecom industries. It is possible that these industries exhibit more dependence on past activity due to unique factors. For the Technology industry, it is possible that new technologies provoke patent and expertise arms races periodically, triggering bursts in M&A activity. The Telecom industry potentially has a regulatory component that triggers a burst in M&A activity, followed quickly by an anti-trust component to suppress sustained periods of high M&A activity to promote equitable market shares and restrict pricing power. Notably, past M&A activity is insignificant in the aggregate model, which contradicts the findings of Barkoulas and Resende, who separately established that persistence and long-term memory are important features of M&A activity in the United States and the United Kingdom (Barkoulas et al., 2001; Resende, 2005).

Industrial Production

For most industries, industrial production was estimated to have a negative impact on M&A activity, contrary to my primary expectation. Although high industrial production is a sign of a healthy economy, the likely explanation for the negative effect is one of timing. As Nelson discovered, industrial production typically peaks after M&A activity does, so when industrial production is high in one quarter, it is likely that M&A activity is already decreasing (Nelson, 1959). In the aggregate model, however, industrial production shows no significance as a driver of M&A activity. The only industry that exhibits industrial production as a positive driver is Telecom.

The negative significance of industrial production as a driver of M&A activity was uncovered in the Consumer Staples, Healthcare, Industrials, Materials and Utilities industries. For the Industrials industry, the reasoning is a direct connection to Nelson's discovery. The Materials industry provides the raw inputs for much of the Industrial industry, and the Utilities industry provides essential services, such as water and electricity, to Industrial consumers. For this reason, it is likely that these industries' revenue cycles imitate industrial production, and thus when industrial production is high, the Materials and Utilities industries are likely healthy and subsequently not as interested in seeking growth opportunities through mergers and acquisitions.

Stock Market Valuations

As expected, stock market valuation has emerged as a very strong positive driver of M&A activity, though, interestingly, for some industries the aggregate stock market health holds more significance than its industry specific stock market index levels. These results are consistent with the previously established notion that the stock market tends to lead M&A activity (Nelson, 1959; Melicher et al., 1983) and that stock markets Granger cause M&A activity (Clarke & Ioannidis, 1996). For the Consumer Discretionary, Financials and Technology industries, the health of their own industry specific S&P indices were more significant than the S&P 500 index. This suggests that these industries are more concerned with the market valuations of their peers than the aggregate market when making M&A decisions.

Notably, the S&P 500 index is the primary driver of aggregate M&A activity in the United States, according to my model, holding tremendous significance. This may indicate that the timing of M&A decisions in the aggregate is primarily valuation and outlook based. When stock market valuations are high, the market has an optimistic outlook and corporations are more comfortable making an acquisition.

Another noteworthy result is that the Energy and Utilities industry models place no significance on stock market valuations as a driver of M&A activity. For the Energy industry, it is plausible that the main driver is geologically event driven, such as the discovery of an abundance of shale or oil in a region already controlled by another company. As for Utilities, mergers and acquisitions may be motivated more by the need for geographical diversification and government regulation, which greatly restricts the amount of expansion opportunities for Utilities companies, so M&A activity would not be quite as in sync with the stock market.

## Industry Uncertainty

Overall, market uncertainty holds little significance across the models but exhibits the expected negative effect where significant. The negative relationship between market uncertainty and M&A activity is consistent with the idea that risk averse corporations tend to shy away from mergers and acquisitions in the presence of high uncertainty. This is largely due to enterprise value in an M&A valuation relying heavily on the ability of the buyer to project the target's future cash flows, as well as the synergies, to predict value creation of the merger pro-forma.

The Telecom and Utilities industries are driven in the negative direction by industry uncertainty, whereas the Consumer Discretionary industry is driven by the change in aggregate uncertainty. The Consumer Discretionary industry consists of companies that produce products or provide services that are non-essential, such as restaurants, vacations, games and new cars. For this reason, the industry is especially sensitive to the aggregate economic cycles. Signs of instability are likely looked at more closely because the industry's performance is highly dependent on the consumer's expectation of the future, causing high market volatility to act as a red flag.

As discussed in the **Description of Data** section, the poor performance of the market uncertainty variables can partially be attributed to the fact that historical volatilities are a poor proxy of future volatility. Ideally, a forward looking measure, such as Black-Scholes implied volatility, should be employed, but sufficient data was not available.

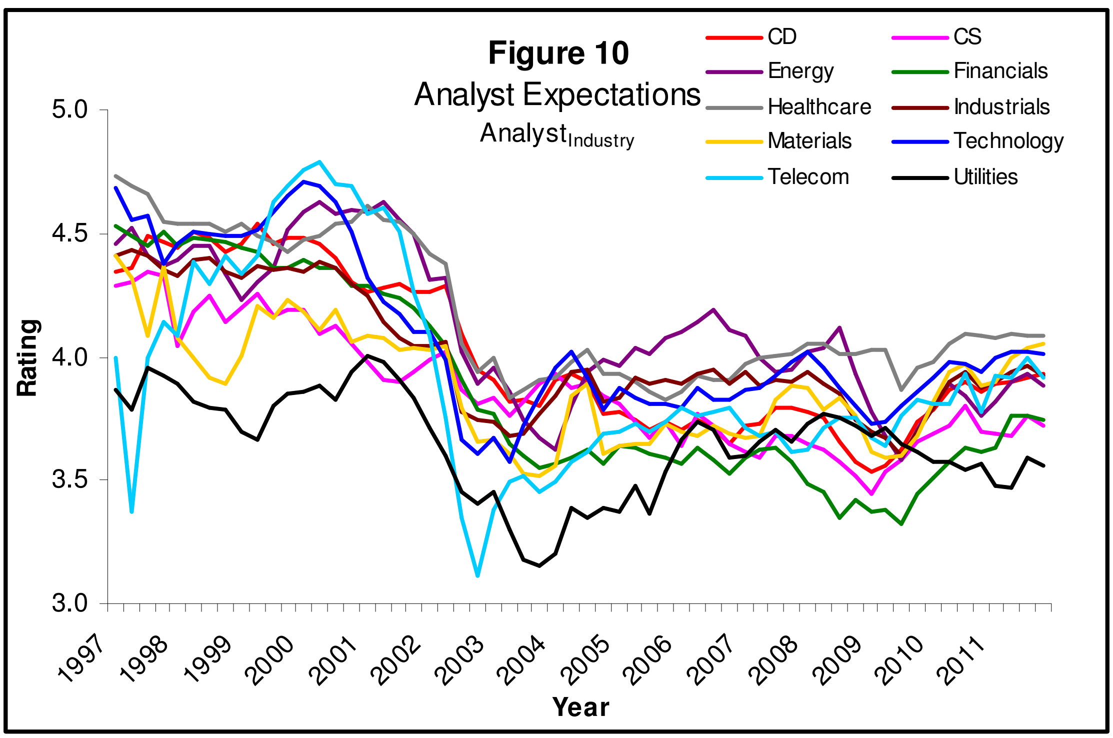
Risk Premiums: Industry Beta

Using the S&P industry indices' market betas as a proxy for the level of the risk premium in an industry led to significance in several models with mixed results. For the Materials and Utilities industries, changes in risk premiums and the level of risk premiums were found to have negative effects on M&A activity, as I had anticipated. For the Consumer Discretionary, Consumer Staples and Healthcare industries, however, the effect of changing risk premiums was in fact positive; an increase in the industry beta in one quarter leads to an increase in M&A activity in the next. This contradicts my expectation, which was an adaptation of Haddad's findings that firms with higher exposure to systematic shocks, or higher market beta, are less likely to be bought out (Haddad et al., 2011). It is possible that increasing risk premiums in these industries signals the need for diversification or better growth prospects, and that some firms utilize M&A as a strong source of inorganic growth and diversification.

Analyst Expectations

As a driver of M&A activity, analyst expectations and changes in expectations showed little significance in most models. In the Energy and Telecom models, however, analyst expectations and changes in analyst expectations emerged as significant, positive drivers of M&A activity, as expected.

Contrary to the findings of Carapeto, analyst expectations exhibited no significance in the aggregate model of M&A activity (Carapeto et al., 2010). Part of the reason is that proxy for analyst expectations, the quarterly change in the number of buy ratings released by equity analysts, is inappropriate and inherently flawed. As discussed in the **Description of Variables** section, analyst coverage has been increasing greatly over time, as has the number of analysts, which creates a major, unwanted increase in their proxy for analyst expectations from quarter to quarter. Although the proxy I created alleviates this issue, another glaring issue remains: there are very few equities covered for much of the sample period, and there is a bias towards corporations with high market capitalization and a history of strong performance. Supporting this claim, the analyst expectation data series never exhibits an equity rating below 3.12, which is a slight buy rating, for any quarter in any industry. Further, the average equity rating over the sample period for each industry hovers around 4, which is a definite buy. As a result, the analyst expectation variable is a fragmented proxy and not very representative of the market as a whole. Below, **Figure 10** plots the analyst expectation variables for each industry, and the optimistic bias is apparent.




Bond Yields

In the models that preferred bond yields to spreads, both Aaa-rated corporate bond yields and the change in treasury note yields emerged as drivers of M&A activity. The relationship between bond yields and M&A activity is negative, consistent with the cost of an acquisition scaling with the cost of capital. Energy M&A activity responds to Aaa-rated bond yields, and, notably, the aggregate model also exhibits corporate bond yields as a driver. This is consistent with the findings of Melicher and Harford but contradicts the early findings of Beckenstein, who uncovered a positive relationship between M&A activity and the cost of capital (Beckenstein, 1979; Melicher et al., 1983; Harford, 2005).

Credit Spreads

The effect of credit spreads on M&A activity proved to be a significant driver in various models, although the results were somewhat mixed. Consistent with my expectation, the Aaa-Treasury spread was uncovered as a negative driver of M&A activity in various industries, including Consumer Discretionary, Materials and Technology. This is likely because wide credit spreads signal pessimistic outlooks as well as uncertainty in the corporate domain, in addition to increasing the cost of M&A transactions. The Baa-Treasury spread on the other hand, was revealed to be a positive driver of M&A transactions in the Consumer Discretionary and Telecom industries, contrary to my expectation. For the Consumer Discretionary industry, the net effect of credit spreads as a driver of M&A is still negative as discussed in the **Analysis** section, but, interestingly, the

Telecom industry exhibits a net positive relationship. This suggests that the Telecom industry may actually prefer to make large capital investments while default risk in corporations is high relative to the United States government.

Surprisingly, the effect of changes in credit spreads was revealed to be a positive driver of M&A activity in several industries, including Healthcare, Industrials, Telecom and Utilities. This suggests that a more ideal environment for M&A transactions in these industries arises when credit spreads are widening, as investors flee corporate bonds in favor of safer government bonds.

## CONCLUSIONS AND SUGGESTIONS FOR FUTURE RESEARCH

The vast domain of M&A drivers research has expanded over time from broad, aggregate analyses of macroeconomic relationships to more focused analyses of fundamental and behavioral drivers. Variable treatment and econometric specifications are inconsistent across published papers, and little attention has been devoted to how M&A activity drivers vary across industries. This paper addressed these issues by posing the following question: *What drives mergers and acquisitions activity in each industry in the United States, and how do those drivers vary across industries?* The econometric models developed in this analysis provided a foothold to tackle this question and establish several trends.

(i) *United States aggregate M&A activity is primarily driven by market valuations and corporate bond yields, despite the importance of various other drivers at the industry level*. Although industry uncertainty, risk premiums, and other drivers have shown significance at the industry level, when aggregated together, these drivers unique to each industry become nearly negligible.

(ii) *M&A activity in some industries is highly driven by macroeconomic and market oriented drivers, whereas others remain largely disconnected from the macro-economy.* Although M&A activity in the Consumer Discretionary, Industrials, Materials, Technology, and Telecommunications industries is relatively well explained using macroeconomic and market-oriented drivers, the Healthcare, Financials and Energy industries are not. These industries must be driven by other such as changes in regulation and technology, some of which may be unique to the industry, such as drug patents in the Healthcare industry and natural resource control in the Energy industry.

(iii) *Aggregate stock market valuations drive M&A in many industries, whereas others are driven by industry specific stock market valuations or are disconnected.* At the aggregate level and in most industries, the health of the S&P 500 is a positive driver of M&A activity, whereas the Consumer Discretionary, Financials and Technology industries are driven more by their industry specific market valuations. The M&A activity of the Energy and Utilities industries, on the other hand, are not significantly driven by market valuations. This suggests that Energy and Utilities corporations do not rely heavily on the stock market to determine whether the environment is ripe for acquisitions, and that they must be more heavily driven by factors unique to the industries.

(iv) *Industry uncertainty is not a significant factor in most industries but drives M&A activity downward.* As expected, industry uncertainty has been uncovered as a driver of M&A activity in a few industries, with high uncertainty leading to lower M&A activity. Once again, this is likely due to the fact that pro-forma analysis and valuation is highly dependent on the predictability of future cash flows, and risk averse acquirers are less likely to engage in investments with uncertain payoffs.

(v) *Increases in risk premiums preface increased M&A activity in some industries and decreased activity in others .* Contrary to my expectation, increasing risk premiums in the Consumer Discretionary, Consumer Staples, and Healthcare industries lead to higher M&A activity. In the Materials and Utilities industries the effect is negative.

(vi) *Analyst expectations do not play a large role in driving M&A activity in most industries, nor at the aggregate level.* Contrary to recent research, analyst expectations contribute minimally to M&A activity. However, the relationship is positive in the two industries that significance arose, Energy and Telecom, which is consistent with previous research, despite the major flaws in the proxy for analyst expectation that was used in previous papers.

(vii) *Aggregate M&A activity is driven downward by high corporate bond yields.* The yields on Aaa-rated corporate bonds has been identified as a primary driver of aggregate M&A activity, with higher yields leading to depressed M&A activity.\

(viii) *M&A activity at the industry level is more reliant on level of credit spreads rather than bond yields, but the effect is different across industries.* In the Consumer Discretionary, Materials, and Technology industries, higher corporate credit spreads exhibited a negative impact, whereas the opposite effect was uncovered in the Telecom industry.

(ix) *Widening credit spreads drive stronger M&A activity at the industry level.* Surprisingly, widening credit spreads tend to preface increases in M&A activity in the Healthcare, Industrials, Telecom, and Utilities industries, despite the pessimism and increased financing costs associated with widening credit spreads. In no industry was the opposite effect been revealed with any significance.

In order to further vet the findings of this paper and contribute further to the domain of M&A drivers research, important considerations and deviations from this paper need to be made:

(i) *Regulatory and industry specific drivers need to be identified and incorporated into the models*. Some models have reasonable fit as purely forecasting based models, but there is much room for improvement, and omitted variables bias is apparent. Some industry models have such poor fit and low variable significance that it is difficult identify specific drivers of M&A activity, such as with the Financials industry.

(ii) *Forward-looking measures of uncertainty need to be employed*. Although historical volatility has shown significance in the expected direction in some models, the role of uncertainty cannot be fully captured using historical data. Forward-looking measures need to be incorporated, such as implied volatility derived from options prices, which would be a significant improvement if sufficient data can be obtained.

(iii) *Unbiased proxies for analyst expectations need to be used*. The proxy for analyst expectation used in this paper is a definite improvement over past research, but the variable is still inherently flawed. As I stated previously, there are very few equities covered for much of the sample period, and there is a bias towards corporations with high market capitalization and a history of strong performance. Over time, I suspect this bias to be transient to a certain extent as analyst coverage improves, but the day that every equity listed on United States exchanges is covered seems far off. Until then, future research should explore alternative proxies for analyst expectations.

(iv) *Alternative data transformations and variable treatments should be considered*. Although I found more success scaling variables by gross domestic product than by using levels or taking first differences of logarithmically transformed data, improvements can almost certainly be made. The main issue with using first differences of logarithmically transformed quarter M&A volume data is that the resulting data series is extremely volatile, whereas the explanatory variables are not, resulting in poor variable significance. Part of the reasoning behind the high volatility is that M&A volume is highly seasonal from quarter to quarter. Adjusting for this seasonality or using yearly M&A data in the specification may result in much better fit and variable significance. Additionally, lag structures and specifications need to be experimented with more thoroughly and optimized accordingly.

(v) *Use longer sample periods.* Much of the data used in this paper extends back much further than the model sample periods. The reason for this is that the analyst expectation proxy could only be derived back to the mid-1990s, due to data insufficiency. If an alternate proxy for analyst expectation is employed, or if the driver is omitted completely, the models could be estimated over a much longer time frame and across more varied economic states and conditions.

This research paper represents an initial attempt at identifying the drivers of M&A activity across industries from a forecasting perspective for comparison purposes. Improvement of this analysis based on the aforementioned suggestions would prove useful for forecasting M&A activity in various industries. If M&A activity can be reliably forecasted, stock price models of investment banks and other financial institutions that provide financing or advise companies on mergers and acquisitions could be developed. Similarly, merger arbitrage could be implemented more reliably in industries that are expected to boom with M&A activity. This paper, combined with past research and the suggested refinements, provides an initial step towards the development of such models, which would prove to be both enlightening and of immense value.

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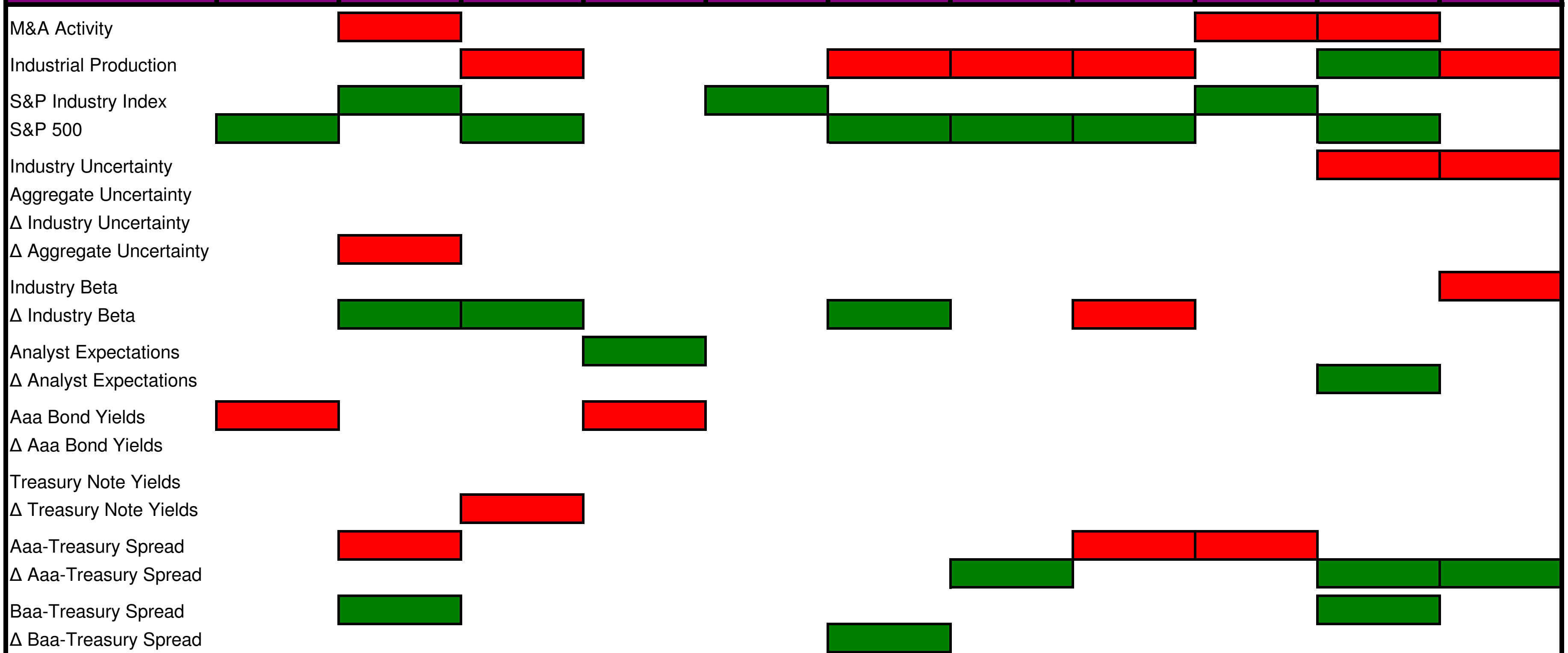
# APPENDIX A

**Figure 9**
**M&A Drivers Across Industries**




| Explanatory Variable[1] | Aggregate | Consumer Discretionary | Consumer Staples | Energy | Financials | Healthcare | Industrials | Materials | Technology | Telecom | Utilities |
|---|---|---|---|---|---|---|---|---|---|---|---|
| *F Statistic*[3] | ***8.76*** | ***7.19*** | *2.56* | *2.23* | *1.56* | *2.56* | ***6.29*** | ***6.43*** | ***14.01*** | ***5.75*** | ***4.39*** |
| *Adjusted* $R^2$ | *0.48* | *0.46* | *0.18* | *0.14* | *0.06* | *0.16* | *0.43* | *0.43* | *0.61* | *0.43* | *0.29* |
| *N* | *59* | *59* | *58* | *59* | *59* | *59* | *58* | *59* | *59* | *58* | *59* |

1. Variables are one quarter lags, Δ represents the first difference operator.
2. Green cells indicate positive, statistically significant coefficients. Red cells indicate negative, statistically significant coefficients.
3. **Bold** indicates statistical significance at the 1% level, red indicates no statistical significance, and the remaining are significant at the 5% level.