What drives mergers and acquisitions in the restaurant industry?

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What drives mergers and acquisitions in the restaurant industry?

by

Jewoo Kim

A dissertation submitted to the graduate faculty

in partial fulfillment of the requirements for the degree of

DOCTOR OF PHILOSOPHY

Major: Hospitality Management

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Ames, Iowa

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ABSTRACT

Mergers and acquisitions (M&A) activity has been growing in the restaurant industry over the past three decades. Recognizing that the importance of M&A has increased as a result of this growth, this study used simulation technique to investigate whether restaurant M&A deals occur in waves. Results indicated that the restaurant industry had three M&A waves between 1981 and 2010.

After confirming the existence of restaurant M&A waves, this study then investigated the macroeconomic determinants of the restaurant waves employing two econometric methods: a distributed lag (DL) model and error correction model (ECM). The results of DL estimation showed that cost of debt negatively affected deal frequency in the long term and inflation had a negative lagged effect on deal frequency. On the other hand, current activity and economic outlook had a significantly positive effect on both deal frequency and deal value. The effect of current activity was lagged while that of economic outlook was lagged and long-term. The results of ECM estimation showed that cost of debt had a negative effect on deal frequency in the short and long term while economic outlook had a significantly positive effect on deal frequency in the long term.

This study contributes to the restaurant industry and its scholarship in several ways. Theoretically, this study extends the restaurant literature by proving the existence of restaurant M&A waves and exploring the relationship between macroeconomic conditions and the restaurant waves. It also examines the applicability of the main theoretical frameworks for general M&A waves in all industries to industry-level waves. Practically, this study can help restaurant firms increase synergistic gains from their M&A deals by identifying important
economic conditions that restaurant firms should take into account when considering M&A deals. Moreover, restaurant firms can use such conditions to predict an appropriate time for their M&A deals.
CHAPTER 1. INTRODUCTION

Mergers and acquisitions (M&A) is a business term referring to the legal consolidation of two firms into one entity (merger) or the takeover of one firm by another (acquisition). M&A has historically been an important strategy in business. Kiymaz (2004) argues that M&A allows firms to increase market share, reduce financing costs, achieve economies of scale, and attain financial stability through diversification. M&A is also effective in increasing firm growth (Ikeda & Doi, 1983; Park & Jang, 2011;) and firm profitability (Gugler, Muller, Yurtoglu, & Zulehner, 2003; Knapp, Gart, & Chaudhry 2006; Ravenscraft, & Scherer, 1989; Neely & Rochester, 1987), and improving market valuation (Chatfield, Dalbor, & Ramdeen, 2011; Demirbag, Ng, & Tatoglu, 2007; Ma, Zhang, & Chowdhury, 2011; Magenheim & Mueller, 1988). For these reasons, firms have increased their use of M&A enormously over the past six decades (Choi & Jeon, 2011). The restaurant industry has contributed to this increase in general M&A activity in all industries (Park & Jang, 2011). According to the Securities Data Corporation (SDC) Platinum database, a total of 2,512 M&A deals were carried out between 1981 and 2011 in the restaurant industry. The total value of those deals was more than $140 billion.

This significant increase in aggregate M&A activity over time has been accompanied by constant fluctuations. This irregular M&A activity creates M&A waves defined as a drastic surge in deal frequency or deal value within a certain period (Golbe & White, 1993; Gugler, Muller, & Yurtoglu, 2006). Researchers who attempted to test the significance of M&A fluctuations (e.g., Golbe & White, 1993; Linn & Zhu, 1997; Resende, 2008; Town, 1992) found that aggregate M&A activity moved in a wave form rather than following a random walk pattern. This statistical verification of M&A waves triggered research on determinants of the waves, because
the repeated appearance of these waves indicated the presence of identifiable forces driving M&A deals (Cook, 2007; Shleifer & Vishny, 2003).

**Statement of Problem**

One research stream on determinants of M&A waves investigates the effect of the macroeconomy on these waves. Researchers attempt to identify the macroeconomic conditions that accelerate M&A activity so as to predict M&A waves based on these significant macroeconomic conditions. Because M&A deals within a wave are more likely to increase participating firms’ market value than those outside of a wave (Maksimovic, Philips, & Yang, 2013), understanding the significant macroeconomic determinants will enable firms to benefit more from M&A deals when economic conditions become better for M&A deals. Firms can maximize their M&A benefits by considering these significant macroeconomic conditions when formulating and implementing their M&A strategy. Prediction of M&A waves would also allow firms to find the optimal timing for M&A deals.

Focusing on general M&A waves, numerous studies have found that stock prices and interest rate significantly and positively affect M&A waves (Beketti, 1986; Benzing, 1991; Corrao, 2012; Haque, Harnhirun, & Shapiro, 1995; Kamaly, 2007; Melicher, Ledolter, & D’Antonio, 1983). Studies have also found that Gross National Product (GNP) or Gross Domestic Product (GDP) are positively significant on M&A waves (Chung & Weston, 1982; Choi & Jeon, 2011; Clarke & Ioannidis, 1996; Golbe & White, 1988; Resende, 2008; Steiner, 1975). However, only sporadic research has been conducted on the relationship between macroeconomic conditions and industry-level M&A waves. Since the 1990s, a growing body of literature (e.g., Andrade & Stafford, 2004; Harford, 2005; Jensen, 2004; Mitchell & Mulherin, 1996; Shleifer & Vishny, 2003) has examined industry-level waves and their determinants,
arguing that the occurrence of industry-level waves is a precondition for general M&A waves and that when several industry-level waves take place concurrently, general waves are created. Based on industrial shock theory and Q-theory, neoclassical studies (e.g., Jensen, 1993; Jovanovic & Rousseau, 2002; Mulherin & Boone, 2000) have examined the effect of industrial characteristics on the corresponding industry-level waves. Behavioral finance studies (e.g., Rhodes-Kropf, Robinson, & Viswanathan, 2005; Rhodes-Kropf & Viswanathan, 2004; Shleifer & Vishny, 2003) have used market timing models to explain industry-level M&A waves as a managerial response to irrational movements in capital markets. However, studies have rarely investigated whether or how macroeconomic conditions cause industry-level waves. The empirical evidence suggesting a significant relationship between macroeconomy and general M&A waves, and that industry-level waves stimulate the general waves, indicates that macroeconomic determinants can be applied to industry-level waves. Moreover, some scholars have claimed that significant macroeconomic conditions may vary across industries due to different industrial characteristics (Corrao, 2012). Therefore, this study examined the effect of macroeconomic conditions on restaurant M&A waves, given the importance of M&A as a strategy in the restaurant business and the restaurant industry in general M&A waves.

**Purpose of the Study**

The purpose of this study was to test for the presence of restaurant M&A waves and, if present, to identify their macroeconomic determinants. First, this study reviewed the literature on M&A wave studies in the general business area. Because of the lack of studies on macroeconomic determinants of industry-level M&A waves, this review process allowed us to understand the research trends and detect drawbacks in previous macroeconomic determinant studies. The research design of this study was based on the review results, in order to address the
drawbacks we found. Second, this study investigated whether M&A waves actually occur in the restaurant industry. As in general M&A wave and other industry-level wave studies, a prerequisite for research on restaurant M&A waves was to demonstrate the existence of the restaurant waves. This investigation not only statistically proved the existence of restaurant M&A waves but also identified the duration of the waves. Third, this study examined the effect of macroeconomic conditions on restaurant M&A waves. A comprehensive set of macroeconomic variables was used to cover various aspects of an economy. The macroeconomic variables’ short- and long-term effects on restaurant M&A waves were explored. Finally, this study investigated whether use of industry-specific or global economic variables which reflect restaurant industry characteristics was more effective in explaining restaurant M&A waves compared to general macroeconomic variables.

**Significance of the Study**

The findings of this study have both theoretical and practical implications. Theoretically, to the best of our knowledge this study provides the first empirical evidence of the presence of restaurant M&A waves and the significant effects of macroeconomic conditions on the waves. This study demonstrates that theories for general M&A waves in all industries can be applied to industry-level waves by identifying macroeconomic determinants of M&A waves in a specific industry context – in this case, the restaurant industry. This study also extends the wave identification technique by comparing overall movements in restaurant M&A activity with their simulated random distributions. Practically, the findings identify the macroeconomic conditions driving M&A waves that restaurant firms should consider in order to maximize synergistic gains from concurrent M&A deals in their industry. Understanding these conditions enables firms not only to assess whether current economic circumstances are suitable for M&A deals, but also to
predict the optimal time for M&A and to adjust the details of their deals according to changing economic conditions during the entire M&A process. Awareness of these conditions will also enable financial analysts and investors to forecast the period of restaurant M&A waves and determine the proper time to invest in the restaurant industry.

**Dissertation Organization**

This study follows the journal paper format, which includes the traditional three chapters (introduction, review of literature, and methodology) and two manuscripts. This study is therefore organized as follows: introduction, review of literature, methodology, first manuscript, second manuscript, and general conclusion. Reference lists are provided at the end of each chapter.

**Glossary of Terms**

Cointegration – a statistical property in which variables’ linear combination is stationary or (more generally) moves closely together (Dritsakis, 2004).

Conglomerate M&A – a M&A deal which combines two unrelated firms in different industries.

Corporate raider – an investor who buys a large stake of undervalued firms’ share and uses the voting rights to require changes in the firms’ leadership, management, and structure with a purpose of increasing the shares’ value.

Cross-border M&A – a M&A deal between two firm in different countries.

Deal frequency – the number of M&A deals completed.

Deal value – the total value of M&A deals completed.

Dot-com bubble – a historic stock market boom between 1997 and 2000 which stock markets rise rapidly with the growth in the internet sector and relevant sectors.
Economies of scale – reduction in cost per unit that firms achieve as their size, output, and operation scale increase.

Horizontal M&A – a M&A deal between firms within the same industry.

Hostile M&A – a M&A deal that a firm is taken over against the target firm’s disapproval and open resistance.

Junk bond – a highly risky fixed-income instrument that provides a high yield and is also called a non-investment-grade bond.

Leverage buyout – an acquisition of a firm funded mostly with loans collateralized by the target’s assets or cash flows.

Macroeconomy – the economic system of a whole country or large region.

Mergers and acquisitions (M&A) – a legal consolidation of two firms into one entity (merger) or the takeover of one firm by another (acquisition).

M&A wave – a drastic surge in M&A deal frequency or deal value within a certain period.

Multidivisional form (M-form) – an organization structure that upper management decides and coordinates the general direction of a firm, while divisional management is given autonomy for daily operations.

Random walk – “an idealisation of a path realized by a succession of random steps,” which “can serve as a model for different stochastic (or random) processes” (Wojnar, 2013).

Simulation – a mathematical technique to “imitate operations of various kinds of real-world processes” (Law & Kelton, 1991).

Type II error – a false rejection of a null hypothesis when an alternative hypothesis is true.

Vertical M&A – a M&A deal in which firms acquired customers and/or suppliers in a single supply chain.
References


CHAPTER 2. REVIEW OF LITERATURE

Mergers and Acquisitions

Mergers and acquisitions (M&A) is described as a business transaction between two firms in which they merge to form a new entity, or in which one firm is acquired by the other. M&A deals have been primarily employed to improve market power, efficiency, and profitability, and thus ultimately maximize shareholders’ value. In M&A, such value creation is pursued by both the target and acquiring firms. Thus, M&A occurs when both firms expect that the value of the restaurant new entity will be greater than the sum of the individual values of the target and acquiring firms. However, M&A deals have not always generated the anticipated gains (Martynova & Renneboog, 2008). Despite inconsistent value-creation outcomes, M&A activity has increased drastically since the 1890s reaching a total deal value of US$3.5 trillion globally in 2014 (Primack, 2015). The restaurant industry is no exception to this trend. According to the SDC Platinum database, global M&A activity in the restaurant industry has increased from 2 deals with a total value of US$375.1 million in 1979 to 446 deals with a total value of US$13.2 billion in 2013. This continued growth in aggregate M&A activity has created M&A waves.

Validation and Identification of Mergers and Acquisitions Waves

Mergers and Acquisitions Wave Validation

It was Nelson’s (1959) study that first suggested the existence of wave patterns in M&A activity. Since then there have been numerous attempts to determine whether M&As come in waves. Shughart and Tollison (1984) investigated cyclical movements in U.S. M&A activity between 1895 and 1977. Their results showed that aggregate M&A activity had a random walk process, which did not support the theory of M&A waves. By contrast, Golbe and White (1993)
found evidence of wave patterns in M&A activity. They examined M&A deals in the mining and manufacturing industries from 1895 through 1989 and showed that those deals followed a wave pattern consistently. Town (1992) as well as Linn and Zhu (1997) used a two-regime Markov switching model to verify M&A waves. Markov switching models have been widely used to analyze time-series showing abrupt changes (Resende, 2008). The two-regime (high and low states) approach tests whether a two-state regime process can explain movements of time-series. Using this model, these studies found that periods of high and low M&A activity alternated and argued that this alternation could be described as a wave. Resende (2008) focused on U.K. M&A deals between 1969 and 2004, also using the Markov switching model; the results were consistent with previous studies using the same model.

**Mergers and Acquisitions Wave Identification.**

In the 1990s scholarly attention began to focus on industry-level M&A waves, with the argument that general M&A waves resulted from the simultaneous occurrence of several industry-level waves (Harford, 2005; Ahern & Harford, 2014). Because there was no consensus on industry-level M&A waves in contrast to general waves, scholars needed to identify the period of industry-level waves before further research on them could be done.

Mitchell and Mulherin (1996) investigated M&A deals between 1982 and 1989 in 51 industries in order to prove the existence of industry-level waves. Their results showed that more than 50% of the total deals in each industry were concentrated in a 24-month period and that the peak periods varied across the 51 industries. Harford (2005) investigated the relationship between industry-level M&A waves and industry shocks from changes in regulation, the economy, and technology. Drawing on Mitchell and Mulherin (1996), he focused on a peak period of 24 months for the identification of industry-level waves. First, he simulated thousands
of distributions of deal frequency with a random process. The actual two-year deal frequency in each industry was then compared with frequency in the simulated peak period. When the actual frequency was higher than the simulated frequency, the actual period was determined to be an M&A wave. His findings reported 35 waves in 28 industries, with the average deal frequency in M&A waves (34.3 deals) more than 4 times that of the average frequency outside of M&A waves (8.5 deals). This study proved that industry-level M&As had a deterministic trend, indicating M&A waves existed at an industry-level.

Another way to identify industry-level M&A waves was proposed by Carow, Heron, and Saxton (2004), who investigated the early-mover advantages in industry-level M&A waves. For their investigation, the authors needed to ensure that the industries examined had M&A waves between 1979 and 1998. They calculated the M&A peak year of each industry in terms of deal frequency, then identified the first and last years of the M&A wave. When an annual deal frequency was less than one third of the peak year, the year was considered as the first or last year. They identified 14 M&A waves in 9 industries during the study period of 20 years. This wave identification method is a relatively simple, but it often fails to identify M&A waves because there is no annual frequency that meets the one third peak criterion.

To investigate the characteristics of the acquiring firms in early and late deals during industry-level waves, Haleblian, McNamara, Kolev, and Dykes (2012) combined the two methods discussed above for industry-level M&A wave identification. Following Carow et al. (2004), the authors identified the industry-level waves by searching for peak, first, and last years. However, they used one half of the peak year instead of one third as the deal frequency criterion for first and last years. The authors then used Harford’s (2005) simulation method to check whether the deal frequency in the peak year could be the result of chance. The deal frequency of
all actual peak years exceeded that of the simulated peak years, confirming the presence of industry-level waves. The study results identified 12 waves between 1984 and 2004 in 12 industries.

**Mergers and Acquisitions Waves**

M&A deals over the past century have occurred in waves (Martynova & Renneboog, 2008). To date, economists and finance scholars have observed six general M&A waves. The scale of those waves has increased in both deal value and deal frequency while deal geography has been diverse. Although these M&A waves have occurred during economic recoveries, different factors have fueled each wave. Identifying the underlying drivers of M&A waves is important in understanding how and why some M&A deal are value-added and others are value-destructive (Martynova & Renneboog, 2008). This expanded knowledge will allow restaurant firms to create more value from successful M&A deals.

The history of these six M&A waves begins in the 1890s. In the first wave, called the Great Merger wave, M&A participants mainly pursued a monopolistic power through horizontal M&As between firms within the same industry (Becketti, 1986). As a result, the wave created industry giants in manufacturing and transportation industries such as steel, telephone, oil, mining and railroads (Lipton, 2006). The ultimate goal of the horizontal M&A deals was to reduce competition in the marketplace and increase product price stability (Lamoreaux, 1985). The capital market crash in 1903 and the outbreak of the First World War ended the first wave.

The second M&A wave occurred in the late 1910s through the 1920s. During this period, anti-trust laws were initiated with a purpose of preventing the abuse of monopolistic power. Consequently, firm expansion was achieved through vertical M&A, in which firms acquired customers and/or suppliers in a single supply chain (Martynova & Renneboog, 2008). For
example, Ford became a major automobile manufacturer by integrating steel mills, ore boats, and iron and coal mines (Lipton, 2006). As a result of increase in vertical M&A, the second wave generated oligopolies, an industry structure in which a small number of leading firms have the most market power (Naveed, Anuar, & Bilal, 2011). These M&As were motivated by economies of scale rather than stabilization of prices (Nelson, 1959; Stigler, 1950).

The third M&A wave occurred in the 1950s and 1960s. It peaked in 1968 and ended in 1973 due to the recession in the world economy caused by the oil crisis (Martynova & Renneboog, 2008). Antitrust laws and business diversification were the main causes of the third wave (Shleifer & Vishny, 1991). In the 1950s, antitrust laws became more restrictive than before discouraging anti-competitive corporate activities. This regulatory force made it more difficult for firms to employ a horizontal expansion strategy but contributed to a substantial increase in conglomerate M&A, which combines two unrelated firms in different industries (Shleifer & Vishny, 1991). During the 1960s, firms mostly employed M&A to seek growth opportunities in new product markets, expanding beyond their core familiar markets (Sudarsanam, 2003). However, it is notable that M&A waves also occurred for business diversification in Canada, Germany, and France even though those countries did not have strong antitrust policies (Matsusaka, 1993). This suggests that managers considered diversification itself as a value-added strategy regardless of the presence or absence of antitrust legislation. Indeed, the third wave of conglomerate M&As was precipitated by managers inspired by new managerial theories supporting diversification, such as the multidivisional form (M-form) and managerial synergy (Sudarsanam, 2003). In an M-form, upper management decides and coordinates the general direction of a firm, while divisional management is given autonomy for daily operations. Divisional flexibility and independence allows firms to maintain their efficiency in handling
diversified products (Chandler, 1962). This advantage of the M-form led many firms to diversify their products through conglomerate M&As (Martynova & Renneboog, 2008). Managerial synergy is achieved when resources obtained from a target firm complement the expertise of the acquiring firm (Matsusaka, 1993). It was not uncommon during this wave for acquiring firms to retain their target company’s management team (human resources) after the deal was completed (Matsusaka, 1993), which provides evidence supporting managerial synergy theory. In addition to these two theories, other scholars have explained the third wave in terms of risk management, arguing that diversified businesses have additional channels of cash flow and therefore can keep higher leverage by reducing the risk of revenue variability (Copeland, Weston, & Kuldeep, 2004; Montgomery, 1994) and bankruptcy (Higgins & Schall, 1975). For all these reasons, conglomerate structures were extensively sought through M&A in the third wave.

The fourth M&A wave began in 1981 and ended in 1989, driven by shifts in antitrust policy, the deregulation of financial markets, and new financial instruments (Martynova & Renneboog, 2008). Debt financing utilizing junk bond markets and leveraged buyouts (LBO) made it easier for acquiring firms to use debt to pay for their M&A deals without their own assets. Therefore, M&A deals became more feasible with the higher leverage (Bhide, 1990). A trend towards de-diversification led to the surge in M&A activity in the 1980s. According to Bhagat, Shleifer, Vishny, Jarrel, and Summers (1990), conglomerate structures favored in the third wave were found to be inefficient in managing diversified businesses. In particular, conglomerate structures proved vulnerable to drastic changes in industrial circumstances including regulation, politics, community, and economy (Mitchell & Mulherin, 1996). These industry shocks resulted in excess capacity, but conglomerate firms were not flexible enough to cope with this problem. Inefficient conglomerate system stimulated the de-diversification trend
in which companies refocused on their core businesses, and M&A was a useful tool for this corporate restructuring (Andrade, Mitchell, & Stafford, 2001; Shleifer & Vishny, 1991). Some firms that failed to recognize the de-diversification trend were forced to restructure through hostile M&As launched by corporate raiders (Martynova & Renneboog, 2008).

The fifth M&A wave took place in 1993 and ended in 2001 by the bursting of the dot-com bubble. It was characterized by its unprecedented magnitude with respect to the deal value and frequency (Lipton, 2006). During the fifth wave, the total number of deals including all transactions in the U.S. and Europe was 235,960, approximately five times that of the fourth wave (Martynova & Renneboog, 2008). The total value was $20 trillion, more than five times that of the fourth wave. Most major M&A deals (e.g., Citibank and Travelers, Chrysler and Daimler Benz, Exxon and Mobil, Boeing and McDonnell Douglas, AOL and Time Warner) were made during the fifth wave (Lipton, 2006). Another distinctive characteristic of the fifth wave was geographical dispersion. In the fourth wave, the number of European M&As was just one third of the number of U.S. deals, but they were roughly equal in the fifth wave (Martynova & Renneboog, 2008). There was also a substantial number of cross-border M&As during the fifth wave (Alexandridis, Mavrovitis, & Travlos, 2012). Globalization forced domestic firms to compete in international markets. Cross-border M&As were widely used as a method of international expansion.

The sixth M&A wave occurred between 2003 and 2007 (Alexandridis et al., 2012). Surprisingly, this wave began only three years after the fifth wave ended. During this wave the proportion of cross-border M&As increased, as it had in the fifth wave, accounting for approximately 40% in the European M&A market and 20% in the U.S. market (Martynova & Renneboog, 2008). Asian firms were also actively involved in cross-border M&As; in particular,
the value of cross-border M&As initiated by Chinese firms increased from US$ 3 million in 2002 to US$ 19 billion in the first half of 2005. However, the overall magnitude of the sixth wave was smaller than the previous fifth wave. It is theorized that managers were doubtful about producing wealth gains from M&A, thus the competition of the M&A market lessened and the premium paid for target firms fell (Alexandridis et al., 2011).

**Determinants of Mergers and Acquisitions Waves**

The presence of M&A waves suggests the existence of a force or forces driving M&A activity. An understanding of these forces can equip firms with better knowledge about industry and business characteristics surrounding M&A activity and the main factors leading to both value-added and value-destructive deals. This knowledge will enable firms to maximize the synergistic effect of concurrent M&A deals. A number of scholars have attempted to discover the determinants of M&A waves. The majority of studies have focused on two categories of determinants: industry/firm-level and macroeconomic.

**Industry/Firm-level Determinants**

According to Gort (1969), M&A activity varies industry by industry and many M&A deals are concentrated in several industries during a certain period, creating an M&A wave. In other words, industry-level waves precede general M&A waves. For example, Mitchell and Mulherin (1996) showed that over half of all M&A deals in the 1980s took place in only 7 out of 51 industries during a 24-month peak period.

There are two popular theoretical frameworks for the occurrence of industry-level waves. Neoclassical models explain industry-level waves as a result of drastic changes in regulation, economic system, and technology (Gugler, Mueller, & Yurtoglu, 2006). Industries experiencing these changes, or industry shocks, tend to end up with excess capacity. This overcapacity leads
them to use M&A for resource reallocation to achieve equilibrium between supply and demand (Jensen, 1993; Komlenovic, Mamun, & Mishra, 2011). In the reallocation process, resources – including tangible and intangible assets – are assigned to more productive and efficient firms (Martynova & Renneboog, 2008). Empirical evidence has supported this theory. According to Hasbrouck (1985), acquiring firms managed their resources more efficiently than target firms. Based on Q-theory, one of the neoclassical theories, Jovanovic and Rousseau (2002) found that firms with higher investment return (or Q ratio) were more likely to acquire firms with lower return. Also, acquiring firms had better performance, more efficient management, and lower leverage than their competitors in the same industry who adopted a non-M&A strategy (Andrade & Stafford, 2004). Harford (2005) emphasized the importance of capital liquidity in the neoclassical explanation of industry-level waves. He argued that sufficient capital liquidity is required for industry shocks to lead to M&A waves, since abundant internal cash reserves or easy access to external financing facilitates M&As when industry shocks cause significant changes within an industry.

The neoclassical model is built up under the assumptions of efficient capital markets and shareholder wealth maximization. By contrast, behavioral models focus only on the assumption of shareholder wealth maximization (Shleifer & Vishny, 2003). Behavioral scholars recognize that the stock market often moves irrationally because it cannot reflect all information immediately. Managers are likely to use these irrational movements to increase their shareholders’ wealth. Market timing theory, an important form of behavioral theory, explains how stock market inefficiency triggers M&A waves (Komlenovic et al., 2011). The theory argues that when the stock market is strong, firms tend to be overvalued. Managers are well aware that the overvaluation is temporary and that the mispriced stock will return to normal
levels in the near future (Gugler et al., 2006). Thus, they try to use their overvalued equity before this happens, to acquire undervalued or less overvalued firms (Shleifer & Vishny, 2003). In this way, temporary overvaluation of equity can be converted into long-term wealth gain for shareholders. Market timing theory also explains the close link between bull markets and M&A waves. A strong market leads to overvaluation of equity; overvalued equity then motivates firms to participate in M&A, primarily by employing the stock payment method (Komlenovic et al., 2011). Harford (2005) confirmed this relationship, showing that stock payment was dominant during M&A waves. Ang and Cheng (2006) and Rhodes-Kropf, Robinson, and Viswanathan (2005) found that acquiring firms using stock payment are more likely to be overvalued than those using cash payment.

Macroeconomic Determinants

Another major focus in researching determinants of M&A waves is macroeconomic circumstances (Komlenovic et al., 2011). Comprehensive economic conditions have been widely used to explain a number of corporate performance measures and activities, including profitability, stock return, credit rating, and M&A activity (Antelo & Mangin, 2010; Athanasoglou, Brissimis, & Delis, 2008; Figlewski, Frydman, & Liang, 2012; Haque, Harnhirun, & Shapiro, 1995). Nelson (1959) first explored the relationship between macroeconomic conditions and M&A waves. He examined the impact of stock market and industrial production on aggregate M&A activity between 1895 and 1956 through correlation analysis. His results found a significant positive correlation between the stock market and wave patterns in M&A activity. Since then, a considerable body of research has investigated the influence of macroeconomic conditions on M&A waves. During our literature review we identified 25 studies on macroeconomic determinants, as summarized in Table 2.1.
Table 2.1

*Studies on macroeconomic determinants of M&A waves*

<table>
<thead>
<tr>
<th>Author</th>
<th>Period studied</th>
<th>Country</th>
<th>Method</th>
<th>Macroeconomic explanatory variables</th>
<th>Identified determinants</th>
</tr>
</thead>
<tbody>
<tr>
<td>Nelson (1959)</td>
<td>1895-1956</td>
<td>US</td>
<td>Correlation analysis</td>
<td>Stock price, industrial production</td>
<td>Stock price</td>
</tr>
<tr>
<td>Weston (1961)</td>
<td>1919-1947</td>
<td>US</td>
<td>Regression</td>
<td>Stock price, industrial production, wholesale commodity prices</td>
<td>Stock price</td>
</tr>
<tr>
<td>Steiner (1975)</td>
<td>1949-1971</td>
<td>US</td>
<td>Regression</td>
<td>GNP, interest rate, stock price</td>
<td>GNP, interest rate, stock price,</td>
</tr>
<tr>
<td>Beckenstein (1979)</td>
<td>1949-1975</td>
<td>US</td>
<td>Regression</td>
<td>GNP, interest rate, stock price</td>
<td>Interest rate, stock price</td>
</tr>
<tr>
<td>Chung &amp; Weston (1982)</td>
<td>1957-1977</td>
<td>US</td>
<td>Regression</td>
<td>GNP, interest rate,</td>
<td>GNP, interest rate</td>
</tr>
<tr>
<td>Geroski (1984)</td>
<td>1895-1979</td>
<td>US / UK</td>
<td>Granger causality test</td>
<td>Stock price</td>
<td>None</td>
</tr>
<tr>
<td>Becketti (1986)</td>
<td>1960-1985</td>
<td>US</td>
<td>Regression</td>
<td>GNP, interest rate, money supply, stock price, domestic</td>
<td>GNP, interest rate, stock prices,</td>
</tr>
<tr>
<td>Polonchek &amp; Sushka (1987)</td>
<td>1948-1979</td>
<td>US</td>
<td>Regression</td>
<td>Interest rate, money supply, unemployment rate, oil price,</td>
<td>Interest rate, unemployment rate, oil price</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>bankruptcy, real expenditure on housing</td>
<td></td>
</tr>
</tbody>
</table>
Table 2.1 (continued)

<table>
<thead>
<tr>
<th>Author</th>
<th>Period studied</th>
<th>Country</th>
<th>Method</th>
<th>Macroeconomic explanatory variables</th>
<th>Identified determinants</th>
</tr>
</thead>
<tbody>
<tr>
<td>Golbe &amp; White (1988)</td>
<td>1940-1979</td>
<td>US</td>
<td>Regression, ARIMA</td>
<td>GNP, interest rate, producer price index (PPI)</td>
<td>GNP</td>
</tr>
<tr>
<td>Guerard (1989)</td>
<td>1895-1979</td>
<td>US</td>
<td>ARMA, Granger causality test</td>
<td>Stock price, Industrial production</td>
<td>None</td>
</tr>
<tr>
<td>Benzing (1991)</td>
<td>1919-1979</td>
<td>US</td>
<td>Regression</td>
<td>Interest rate, stock price, unemployment rate</td>
<td>Interest rate, stock price, unemployment rate</td>
</tr>
</tbody>
</table>
Table 2.1 (continued)

<table>
<thead>
<tr>
<th>Author</th>
<th>Period studied</th>
<th>Country</th>
<th>Method</th>
<th>Macroeconomic explanatory variables</th>
<th>Identified determinants</th>
</tr>
</thead>
<tbody>
<tr>
<td>Cook (2007)</td>
<td>1975-2005</td>
<td>UK</td>
<td>GARCH, Granger causality test</td>
<td>Industrial production</td>
<td>Industrial production</td>
</tr>
<tr>
<td>Choi &amp; Jeon (2011)</td>
<td>1980-2004</td>
<td>US</td>
<td>VAR, Granger causality test</td>
<td>GNP, interest rate, money supply, stock price, corporate cash flow</td>
<td>GDP, interest rate</td>
</tr>
</tbody>
</table>
In these studies, the most frequently-examined macroeconomic variable was stock price. The association of this macroeconomic variable with M&A waves was modeled based on the expectations theory. According to this theory, economic growth expectation is the main driver of aggregate M&A activity. When growth expectation is high, M&A waves are likely to occur (Benzing, 1993). High growth expectation means that an economy will be buoyant and therefore will experience a deficiency in supply due to increased demand (Fama, 1981). Firms with high growth expectation for future economy are likely to add capacity to take advantage of the opportunity offered by supply shortage. They make extensive use of M&A to increase capacity in the short term. Growth expectation in these studies has mainly been represented by stock prices. Based on this theory, the effect of stock prices has been investigated in a number of empirical studies (e.g., Benzing, 1991; Corrao, 2012; Haque et al., 1995; Resende, 2008). Their results have consistently presented that the effect is positively significant (Choi & Jeon, 2011; Kamaly, 2007; Shleifer & Vishny, 2003).

The capital market theory argues that M&A waves are closely associated with interest rate. A low interest rate reduces the cost of raising external funds and further encourages business investments, including M&A. In addition, the lower the interest rate, the higher the cash flows from investment. As a result, it is likely that firms perform investment activities due to increases in expected return on investment (ROI). In sum, low interest rates lead to reduced financing costs and increased ROI, which facilitates M&A deals. While a number of M&A studies (e.g., Choi & Jeon, 2011; Melicher, Ledolter, & D’Atonio; 1983 ; Steiner, 1975; Yagil, 1996) have empirically supported the impact of interest rate, its direction has been inconclusive. Benzing (1991) and Choi and Jeon (2011) found a negative relationship between interest rate and M&A waves, which corresponds to the general expectation of the relationship. On the other
hand, some studies (e.g., Beckenstein, 1979; Steiner, 1975) reported that interest rate positively affected M&A waves.

The economic disturbance theory is also an important conceptual framework for describing the relationship between current economic conditions and M&A waves. According to Gort (1969), M&A takes place when potential investors’ valuation of a business is higher than that of its existing shareholders. Stakeholders tend to estimate future cash flows of a business differently from investors. When an economy grows, the variation in the stakeholders’ estimated return enlarges, creating a valuation discrepancy between shareholders and investors. Thus, as economic activity improves, M&A waves are more likely to occur. Gort (1969) and Resende (2008) tested this relationship based on the economic disturbance theory using stock prices and gross domestic product (GDP) as proxies for current economy. Their results showed that current economic conditions had a significant effect on M&A waves.

The effect of current economic conditions can be also explained by the merger activity-economic prosperity theory introduced by Reid (1968). This theory views current conditions to reflect market expectations of future economy. In this sense, strong current economy can be interpreted as market’s optimistic expectation for strong future performance. Using this theory, Melicher et al. (1983) investigated the effect of current economy represented by industrial production, but the effect was not significant. Considerable efforts have been devoted to analysis of the relationship between industrial production and M&A waves, but the analyses did not yield consistent results. Cook (2007) and Finn and Hodgson (2005) found a positive association of industrial production with M&A waves. In contrast, Argus & Finn (1991), Corrao (2012), and Guerard (1989) failed to find evidence of this association.
Capacity utilization has been used to proxy current economy in the previous studies (e.g., Becketti, 1986; Benzing, 1991). The relationship between capacity utilization and M&A activity is controversial. According to neoclassical researchers, drastic changes in industrial business conditions lead industries to have overcapacity, and firms within the affected industries become actively involved in M&A activity to remove this excess capacity (Jensen, 1993). Other researchers argue that M&A is primarily used by firms that seek to increase their operating capacity in a short period of time in order to take advantage of an expected economic boom (Komlenovic et al., 2012). Despite these conflicting arguments, the effect of capacity utilization on M&A waves was found to be mainly positive (Becketti, 1986; Komlenovic et al., 2011).

Besides the macroeconomic conditions discussed above which have a theoretical foundation, unemployment rate, money supply, bankruptcy, and inflation have also been explored as determinants of M&A waves. While unemployment rate were found to be significantly related to M&A waves (Benzing, 1993; Polonchek & Sushka, 1987), money supply, bankruptcy, and inflation were not (Becketti, 1986; Choi & Jeon, 2011; Golbe & White, 1988; Resende, 2008).

In the previous studies on macroeconomic determinants, the explanatory economic variables were mostly pre-selected rather than using a variable selection process. Several economic variables such as stock price, interest rate, and GDP were theoretically supported, but the other variables were arbitrarily chosen based on untested assumptions, which may result in omitted variable bias. When influential variables are omitted in a model, an endogeneity problem is likely to arise in which dependent variables are correlated with an error term and the effects of dependent variables are over- or underestimated. Moreover, use of only a few macroeconomic variables as independent variables make it difficult to fully recognize the effects of economic
activity as a whole on M&A wave. This leads to poor model fit and reduces the model’s explanatory power. It is therefore necessary to examine a more comprehensive set of macroeconomic variables chosen via objective variable selection processes in order to precisely estimate their true effect and identify significant economic forces on M&A waves.

Macroeconomic determinants of M&A waves have been investigated primarily in the context of general economy covering all industries. Despite the importance of industry-level waves in initiating general M&A waves, only a few recent studies (e.g., Corrao, 2012; Komlenovic et al., 2011) have highlighted the positive link between macroeconomic conditions and industry-level waves. Komlenovic et al. (2011) indicated that industry-level M&A deals were significantly linked to economic cycles in several industries. Corrao (2012) showed that the effect of macroeconomic variables was heterogeneous between industries and that each industry had different macroeconomic determinants of its wave. The different effect of macroeconomic conditions on industry-level waves may result from unique industrial features. Therefore, identifying the macroeconomic conditions facilitating waves in each industry broadens our understanding of industrial uniqueness and how it affects industry-level M&A activity. Moreover, it can help identify the common economic conditions that significantly influence M&A waves across industries.

To explain the relationship between macroeconomic conditions and M&A waves, various statistical methods have been employed over the past six decades. From the 1950s through the 1970s, determinants studies (e.g., Steiner, 1975; Weston, 1961) mainly employed multiple regression analysis. It was the 1980s for researchers to consider time series characteristics of the data examined. The attempt to address the endogeneity problem caused by serial correlation began during this period. For example, Benzing (1993) incorporated an autoregressive term into
the regression model to avoid serial correlation and found the coefficient of the autoregressive term to be significant. Clark, Chakrabarti, and Chiang (1988), Guerard (1989), and Haque et al. (1995) adopted time series analysis to construct more optimal models to fit the data. These time series models included autoregression (AR) and autoregressive and moving average (ARMA). They also used the Grange causality test to determine the predictive power of macroeconomic variables on M&A waves. In the mid-1990s researchers began to develop time series models based on econometrics forms such as vector autoregression (VAR) and vector error correction model (VECM) (e.g., Choi & Jeon, 2011; Clarke & Ioannidis, 1996; Finn & Hodgson, 2005). Using econometric time series models, researchers could investigate the reciprocal relationships of variables. For example, Finn and Hodgson (2005) analyzed the relationships between five economic variables and aggregate M&A activity. They found that industrial production affected M&A activity in the short term while stock prices and M&A had a significant impact on interest rate, capital expenditure, and industrial production in the long term. Resende (2008) used a non-linear technique known as the two-state Markov switching model to analyze wave patterns of M&A activity and investigate whether the wave patterns were related to macroeconomic conditions. His results provided evidence of a significant influence of stock prices, money supply, and GDP on M&A waves.

Macroeconomic variables are indexes which measure various aspects of an economy. Although each variable focuses on a specific economic activity, it is impossible for macroeconomic variables to be studied completely exclusive of other macroeconomic variables because there are very complex interdependencies between the economic activities represented by the macroeconomic variables (Cheng, 1995). Thus, as the number of independent macroeconomic variables in a model increases, correlation between the variables is likely to arise
and result in problems of multicollinearity. However, many previous M&A wave studies on macroeconomic determinants did not take this problem into account in developing their models. The presence of multicollinearity lowers the predictive power of individual independent variables leading to a type II error in which a null hypothesis is falsely not rejected when an alternative hypothesis is true. Accordingly, multicollinearity problems must be dealt with when examining a comprehensive set of macroeconomic variables.

**Mergers and Acquisitions Studies in the Restaurant Industry**

Use of M&A as a strategic tool has increased in the restaurant industry, but little scholarly attention has been paid to M&A given its importance in the industry. A few M&A studies may be found in the restaurant literature. The research topic of those studies was value creation via restaurant M&A activity. Park and Jang (2011) reported that the sales growth of acquiring restaurant firms (23.0%) was significantly higher than non-acquiring restaurants (6.0%) in the short term, but the M&A effect on sales growth did not last more than a year after the deal was completed (acquiring firms 5.1% and non-acquiring firms 5.3%). Chatfield, Chatfield, and Ramdeen (2011) found that the cumulative abnormal returns (CARs) of 171 acquiring restaurant firms (1.19%) was positive, but insignificant for two specific days: one day before the announcement of the M&A and the day of the announcement. On the contrary, 26 target restaurant firms experienced on average significant, positive CARs (13.98%) in the same period.

Lack of available M&A data has led hospitality researchers to combine restaurant data with data from other hospitality industries including lodging and gaming. For example, Oak and Andrew (2006) examined M&A deals in the lodging, casino, cruise and restaurant industries to analyze the impact of information asymmetry on stock trading activities when an M&A deal was
announced. Sheel and Nagpal (2000) looked at M&A deals of restaurant and lodging firms to investigate the short- and long-term effects of M&A on equity value performance. Their results failed to show a significant relationship between M&A and equity value in the short term (1.13% in 1 month after M&A) while the long term M&A effect was found to be significantly negative (-176.65% in 36 months after M&A).

The effect of M&A payment method on value creation has often been explored with mixed M&A data. In their investigation of M&A deals of restaurant and lodging firms between 1980 and 2004, Oak, Andrew, and Bryant (2008) found that the financing method of a given M&A deal was determined by debt ratio, capital expenditure ratio, and firm size. They also found that cash financing was the preferred payment method in hospitality deals. Chatfield, Chatfield, and Dalbor (2012) examined the relationship between M&A payment method and abnormal returns of hospitality acquirers including lodging, restaurant, and gaming firms. They found that acquirers using cash financing had significant positive returns (1.58%), but that the returns were not significant when the deals were paid for with stock or a mix of stock and cash.

Although the restaurant industry primarily used cash financing (41.2% of all restaurant M&A deals), 66.7% of all M&A deals that used stock financing took place in the restaurant industry.

Kim and Arbel (1998) constructed a binomial logistic model to predict hospitality M&A targets in three sub-industries: restaurant, lodging, and gaming. Their model provided reliable outcomes by correctly predicting 79% of actually-acquired firms and 74% of non-targets. Their model’s prediction accuracy was similar to the accuracy rate of previous M&A target prediction models, which ranged from 70% to 90% (Palepu, 1986). Four factors – size, price-to-book ratio, growth, and capital expenditure – were found to be critical in identifying targets and non-targets.
However, to the best of the author’s knowledge, no study has focused on M&A waves in the restaurant industry. Annual number and value of restaurant M&A deals between 1981 and 2011 are shown in Figures 2.1 and 2.2. Similar to the general M&A waves discussed earlier, the figures show at least one restaurant wave in every decade. This provides empirical evidence of the contribution of the restaurant industry to the general M&A waves and therefore suggests that determinants of general M&A waves may be applicable to restaurant waves.

M&A has long been used to improve corporate efficiency and performance and increase shareholders’ value. Use of M&A has enormously increased over the past century, giving rise to M&A waves. Understanding the determinants of M&A waves is critical in making correct M&A decisions. This study investigated whether M&A waves are present in the restaurant industry and what if any macroeconomic conditions serve as determinants.

![Figure 2.1. Annual number of M&A deals in the U.S. restaurant industry, 1981 - 2010](image-url)
Figure 2.2. Annual value of M&A deals in the U.S. restaurant industry between 1981 and 2010.

Annual value is expressed in billions of dollars.
References


CHAPTER 3. METHODOLOGY

The purpose of this study was to verify the existence of mergers and acquisitions (M&A) waves in the restaurant industry and identify their macroeconomic determinants. First, this study tested for the presence of restaurant M&A waves by comparing actual restaurant M&A deals based on historical data with a randomly generated set of deal data. Second, this study investigated which economic conditions trigger restaurant M&A waves and explored their short- and long-term relationships using a distributed lag (DL) model and error correction model (ECM).

Identification of Restaurant Mergers and Acquisitions Waves

To determine the presence of restaurant M&A waves, this study employed simulation techniques. Simulation is described as a mathematical technique to “imitate operations of various kinds of real-world processes” (Law & Kelton, 1991). Simulations can computationally produce approximate behaviors of the processes of interest, allowing researchers to analyze complex real situations by exploring similar virtual situations constructed in quantifiable form (Anderson, 2004; Perros, 2003). An additional benefit of simulated processes is that they can be controlled by selectively modifying important variables and thus researchers can create desired behaviors for virtual experiments. (Kelton, Sadowski, & Sadowski, 2002; Perros, 2003). Simulations can also reveal consistent patterns by re-creating a certain situation multiple times (Law & Kelton, 1991). This advantage helps researchers accurately predict the outcome of changes in the modeled situation (Evans & Olson, 1998). Based on these benefits, simulation techniques have been widely used for statistical analysis (Chiodi, 2012) and are viewed as an effective and convenient way to analyze data whose distribution is unknown. Development of new simulation techniques such as Monte Carlo, Markov chains, and Gibbs sample allows numerical integration,
optimization, and empirical evaluation of the goodness of an analytical asymptotic approximation (Chiodi, 2012).

To prove that the restaurant industry exhibits wave patterns in its aggregate M&A activity, it is necessary to show that actual deal frequency cannot occur by accident. For our purposes, simulation generated distributions of random M&A activity. The simulated distributions were compared with the actual frequency of restaurant M&A deals. Because the simulated distributions exhibit random behavior which appears when events occur spontaneously without any significant factor, the comparison results can provide evidence of restaurant M&A waves.

This study used simulation analysis based on Harford (2005) because not only can Harford statistically verify the presence of M&A waves, it can also identify the periods of the waves. Moreover, this simulation method has been used in numerous previous studies on industry-level M&A waves (e.g., Alexandridis, Mavrovitis, & Travlos, 2011; Duchin & Schmidt, 2013; Sonenshine & Feinberg, 2014). A statistical package of R was used to simulate distributions based on the aggregate deal frequency for each decade. Before the simulation, according to Harford’s (2005) method, the sample was split into three decades (the 1980s, 1990s, and 2000s). The deal frequencies for each decade were 323, 654 and 355, respectively. The distinct increase in the number of restaurant M&A deals in each decade corresponds with the general U.S. M&A waves. Through the simulation, 1,000 distributions were generated for each decade. In the simulation, each M&A deal was randomly assigned to a quarter in a decade to make the distributions random. In other words, each quarter has the same probability of being assigned a deal (1/40). As a result, 1,000 simulated distributions for each decade had the same deal frequency as the actual restaurant M&A frequency in the corresponding decade. Unlike
actual M&A deals, however, M&A data in the simulated distributions were randomly
distributed. From each simulated distribution, this study calculated the highest two-year
concentration, yielding a total of 1,000 highest two-year concentrations for each decade. Next, a
new distribution of the two-year peak period was developed based on the 1,000 highest two-year
concentrations. This uniform two-year peak distribution was compared with actual deal
frequency for any continuous two-year period in a decade (e.g., first quarter through eighth
quarter or second quarter through ninth quarter). When an actual two-year deal frequency was
more than the 95th percentile from the simulated two-year peak distribution, the actual two-year
period was considered as a restaurant M&A wave. The comparison results showed that each
decade had one restaurant M&A wave; specifically, the 1990s wave occurred the third quarter
1987 to the second quarter 1990, the 1990s wave occurred the fourth quarter 1994 to the first
quarter 1999, and the 2000s wave occurred the first quarter 2006 to the fourth quarter 2008.

The Kolmogorov-Smirnov (K-S) test was used to confirm the results from the above
analysis. The K-S test is a general non-parametric method of comparing the cumulative
distribution functions (CDFs) of two data sets. Harford’s (2005) simulation method identifies
M&A waves by comparing higher deal frequencies in the actual and simulated distributions,
whereas the K-S test investigates the overall equality of two data sets. Their equality is tested by
measuring the distance between CDFs of the two data sets. The K-S statistic for each of three
decades indicates whether to reject the null hypothesis: the distribution of actual restaurant M&A
deal frequency is the same as the simulated randomly-generated distributions of the actual deal
frequency at the level of 5% (α=0.05). The K-S test results showed that the restaurant M&A
deals did not occur by chance, which implies the presence of restaurant M&A waves.
Both Harford’s (2005) simulation method and the K-S test empirically proved that the restaurant industry had M&A waves. The empirical evidence of restaurant M&A waves provided the background for further studies on macroeconomic determinants of these waves.

**Exploratory Factor Analysis**

Because the presence of restaurant M&A waves was confirmed, this study investigated the effect of macroeconomic conditions on the waves. First, this study used exploratory factor analysis (EFA) to analyze the macroeconomic dataset including 16 variables. EFA is a multivariate analysis tool which can be used to discover the underlying nature of variables of interest. Through EFA, highly correlated variables are grouped into a factor to represent a fundamental dimension of data (Hair, Tatham, Anderson, & Black, 1998). By creating a map of the interrelationships of the variables analyzed, EFA achieves data summarization minimizing the loss of the original characteristics of the variables. In this analytic process, EFA not only removes serious correlations between the variables but also reduces the dimensions of the dataset (Ary, Jacobs, & Sorensen, 2010). When multivariate techniques are employed, the number of variables examined increases. As more variables are added to a model, it is more likely that one or more of the variables will be interrelated. Inclusion of many correlated variables can cause multicollinearity problems. Also, too many dimensions in the large dataset will make it difficult to analyze the relationships between variables and to interpret the results of data analysis. EFA addresses those potential problems simultaneously by identifying a smaller number of latent factors, each of which has similar profiles (Dwyer, Gill, & Seetaram, 2012). Besides data summarization and data reduction, another use of EFA is for variable selection for measurement of complex constructs and scale development. In particular, this technique is useful when the dimensionality of data and its structural composition are not well known. Because EFA can
reveal the primary variables consisting of an unobservable factor without conceptual basis for their relationship, it builds a foundation for additional study using confirmatory factor approach to investigate whether the variables are appropriately representing the unobservable factor (Hair et al., 1998).

The macroeconomic variables used in this study may be closely interrelated (Cheng, 1995). The macroeconomic variables are the economic indices developed to measure a broad range of economic activity. Because many economic activities are interdependent, the macroeconomic conditions measured by economic indices may overlap, which may result in multicollinearity. Consequently, EFA is necessary to uncover the real structures of macroeconomic variables while avoiding multicollinearity. Indeed, extant finance studies (e.g., Bilson, Brailsford, & Hooper, 2001; Liow, Ibrahim, & Huang, 2006) have widely employed EFA to deal with large macroeconomic datasets in modeling the impact of economic conditions on capital markets. For example, Panetta (2002) performed maximum likelihood EFA to investigate the relationship between the macro-economy and stock returns. He extracted 5 factors from 14 macroeconomic variables, including industrial production, inflation, and money growth, and regressed them against abnormal stock returns over the average market return. His findings showed that the relationship of the selected macroeconomic factors and stock returns varied across the several periods examined.

In the present study, the variables examined were economic time-series data that might be non-stationary over time, violating the Independent and Identically Distributed (IID) assumption for factor analysis (Gilbert & Meijer, 2005). Thus, it was necessary to check the stationarity of each variable through a unit-root test. Using the Augmented Dickey-Fuller (ADF) test, this study revealed that most of the macroeconomic variables (except the three interest rate variables) had a
unit root, indicating that the variables were non-stationary. This study took the first difference of the macroeconomic variables with a unit root in order to make the variables stationary and further validate the use of EFA on the variables. In addition, this study performed logarithmic transformation of the entire macroeconomic dataset to ensure that the macroeconomic variables had more normally-distributed and equally-variant shapes.

The first-differenced macroeconomic variables were the changes in the natural logarithm of the variables at time $t$. The quarterly changes of the logarithmically-transformed macro variables were calculated as follows:

$$\Delta MACRO_{i,t} = \ln(MACRO_{i,t}) - \ln(MACRO_{i,t-1})$$

(1)

where $\Delta = $ a first-difference operator; $MACRO_{i,t} =$ macroeconomic variables with a unit root at time $t$; and $MACRO_{i,t-1} =$ macroeconomic variables with a unit root at time $t-1$.

The interest rate variables without a unit root were the natural logarithm of the variables at time $t$. The quarterly levels of the logarithmically-transformed interest rate variables were calculated as follows:

$$INTEREST_{j,t} = \ln(INTEREST_{j,t})$$

(2)

where $INTEREST_{j,t} =$ macroeconomic variables without a unit root at time $t$.

Following data transformation, this study performed Principal Axis Factoring for EFA. To determine the number of factors, Kaiser’s Criterion and scree plots were employed; based on these two tests, four factor solution was recommended. Direct Oblimin method was used to rotate the factor loadings. This is a non-orthogonal rotation method that can be used for correlating extracted factors. Direct Oblimin yields the same result as Varimax, an orthogonal rotation, if the factors are not correlated. Each latent factor named according to the underlying characteristics of several macroeconomic variables with high factor loadings that represented the
factor. The four factors were as follows: Factor 1 Current Activity (CA), Factor 2 Cost of Debt (CD), Factor 3 Economic Outlook (EO), and Factor 4 Inflation (INF).

**Distributed Lag Model**

This study explored the relationship between macroeconomic conditions and restaurant M&A waves using distributed lag (DL) models, which includes lagged independent variables in the analysis. Using this model, this study was able to investigate the short- and long-term effects of macroeconomic factors on restaurant M&A waves. Two estimation models were developed with two alternative dependent variables: the quarterly frequency and value of restaurant M&A deals. The four macroeconomic factors extracted from EFA were used as the independent variables in both models. The lag length of the variables was determined by comparing the Akaike Information Criterion (AIC) of the models with different lags (Pagano & Hartley, 1981). Because the four-lag model was estimated to be the best fit, the lagged macroeconomic factors from time t-1 to t-4 were added to the models. Dummy variables for the first, second, and third quarter of each year were entered into the model to control for seasonality.

The DL models were as follows:

\[
DF_t = \beta_0 + \sum_{i=1}^{4} \sum_{j=0}^{4} \beta_i MACRO_{F_i,t-j} + \sum_{k=1}^{3} QUARTER_k
\]  \hspace{1cm} (Model 1)

\[
DV_t = \beta_0 + \sum_{i=1}^{4} \sum_{j=0}^{4} \beta_i MACRO_{F_i,t-j} + \sum_{k=1}^{3} QUARTER_k
\]  \hspace{1cm} (Model 2)

where \(DF_t\) = deal frequency of restaurant M&As at time \(t\), \(DV_t\) = logarithmically-transformed deal value at time \(t\), \(MACRO_{F_i,t}\) = four macroeconomic factors at time \(t\), and \(QUARTER_k\) = dummy variable for the first, second, and third quarter of a year.

This study tested for serial correlation in the models because the dependent variables were a time-series. In the presence of serial correlation, coefficients of dependent variables estimated by ordinary least squares (OLS) may be unbiased and consistent, but inefficient.
Moreover, there is a greater tendency to underestimate standard errors and overestimate $R^2$. The Durbin-Watson (D-W) test was employed to check whether the residuals of the models were serially correlated. The test results showed that serial correlation existed in both DL models. Therefore, this study applied Prais-Winsten estimation to the models to control for serial correlation, following the recommendation of Hansen and Huang (1997). Prais-Winsten estimation uses generalized least squares (GLS) to handle the serial correlation of AR(1) type in a linear model (Judge, Griffiths, Hill, Lütkepohl, & Lee, 1985; Prais & Winsten, 1954). When linear regression is serially correlated:

$$Y_t = \alpha + X_t \beta + \varepsilon_t$$

(3)

where $Y_t$ is a time-series dependent variable at time $t$, $\beta$ is a vector of coefficients, $X_t$ is a matrix of independent variables at time $t$, and $\varepsilon_t$ is an error term at time $t$, the error term can be written as:

$$\varepsilon_t = \rho \varepsilon_{t-1} + e_t$$

(4)

where $|\rho| < 1$ and $e_t$ is white noise. The Prais-Winsten estimation procedure can be used to transform regression coefficients by subtracting the lagged regression equation multiplied by $\rho$ (Eq. 5) from the original equation:

$$\rho Y_{t-1} = \rho \alpha + \rho X_{t-1} \beta + \rho \varepsilon_{t-1}$$

(5)

$$Y_t - \rho Y_{t-1} = (1 - \rho) \alpha + (X_t - \rho X_{t-1}) \beta + v_t$$

(6)

where $v_t = \varepsilon_t - \rho \varepsilon_{t-1} = \rho \varepsilon_{t-1} + e_t - \rho \varepsilon_{t-1} = e_t$. Through this sequence of procedures, the linear regression model with first-order serially correlated residuals is corrected. Accordingly, simply applying OLS to the transformed variables is appropriate (Davidson & MacKinnon, 1993).
Selection of Variables

Macroeconomic variables for factor analysis were selected based on their relationships with M&A deals. Previous M&A wave studies (e.g., Melicher, Ledolter, & D’Antonio, 1983) have extensively examined stock price and interest rate to identify the macroeconomic determinants of M&A waves, using them to represent expectation of future economy and capital market conditions, respectively. The expectations theory and the capital market theory support the effect of these macroeconomic variables. The findings of these earlier studies show that positive prospects for economic growth and low cost of debt substantially increase M&A deals, creating M&A waves (Choi & Jeon, 2011; Komlenovic, Mamun, & Mishra, 2011). Based on empirical evidence and theoretical foundations drawn from previous studies, the present study included stock prices and interest rate in the macroeconomic data. Two types of index were used to measure stock price: the Dow Jones Index (DJI), consisting of 30 industry-leading firms, and Standard & Poor’s 500 (S&P), comprised of 500 large firms. All firms in these two indices are listed in either the New York Stock Exchange (NYSE) or the National Association of Securities Dealers Automated Quotations (NASDAQ). Interest rate variables were 10-year Treasury bond rate, 3-month Treasury bill rate, and Federal Funds rate. Treasury bond rate is an indicator of long-term interest rate while Treasury bill rate represents short-term rate.

Current economic activity is positively related to general M&A waves (Gort, 1969; Golbe & White, 1988). This relationship also has a theoretical foundation (economic disturbance theory). GDP is a typical measure of current economic activity. A high level of GDP signifies strong economic growth which can lead to M&A waves (Choi & Jeon, 2011; Clarke & Ioannidis, 1996; Resende, 2008). The macroeconomic dataset for this study included real GDP (i.e., GDP adjusted for inflation).
Employment is also an indicator of current economic activity. It is significantly associated with household income (DiPrete & McManus, 2000) which directly impacts the restaurant industry (Denizci, 2007). This study used two employment-related variables. The total number of employees is positively linked to the economy and thus affects M&A waves. This employment variable was seasonally-adjusted for data analysis. Unemployment rate is negatively correlated with the economy: the stronger the economy, the lower the unemployment rate.

Consequently, it is likely that low unemployment rate drives M&A waves. For this study, the quarterly unemployment rate was calculated as the average of three monthly rates in a quarter.

Industrial production and capacity utilization are two other economic variables that can be used to measure current economic conditions. While the effect of industrial production on M&A activity is inconclusive, the effect of capacity utilization is straightforward: as capacity utilization increases, so does M&A activity. In this study, capacity utilization was presented as a percentage scale of the U.S. domestic economy and industrial production was measured as the seasonally-adjusted output of the selected industrial areas including manufacturing, mining and utilities.

Money supply refers to the total amount of liquid assets in an economy. According to the Fisher effect (Fisher, 1930), money supply directly affects inflation and inflation determines the nominal interest rate in the long term given the relationship that real interest rate equals the nominal interest rate less the expected inflation rate. Additionally, money supply is related to the opportunity cost of cash in relation to alternative sources of financing for investment activity. Real growth in liquidity reduces the opportunity cost of cash (Fishman, 1989) while encouraging M&A deals through cash offers (Resende, 2008). Alexandridis et al. (2011) argue that easy access to abundant funds provided by a growing money supply is the main driver of the sixth
M&A wave (2003-2007). Harford (2005) claims that sufficient liquidity is necessary for the occurrence of industry-level waves. For this study, the measure of money supply was seasonally-adjusted M1 and M2. M1, a traditional liquid measure, consists of currency, travelers’ checks, and demand deposits. M2 combines M1 and various substitutes for M1 including savings deposits, time deposits, and money-market deposits.

Inflation captures changes in general price level for commodities in an economy. According to Golbe and White (1988), inflation reflects structural changes in business conditions. High inflation indicates drastic changes in existing businesses. They also claim that high inflation increases uncertainty in existing businesses and further creates new business opportunities. In this sense, inflation is expected to be positively associated with M&A waves (Golbe & White, 1988). This linkage between inflation and M&A waves can be viewed from a different angle. Inflation influences the expected cash flow generated from a business or an investment (Panetta, 2002). The expected cash flow increases when inflation is taken into account. Due to increased cash flow, net present value (NPV) for investment projects like M&A is more likely to be positive. The consumer price index (CPI) and producer price index (PPI) were used as proxies for inflation in this study. Quarterly values of CPI and PPI were computed by averaging monthly values for these variables.

An economy is significantly affected by energy-related commodities such as oil, natural gas, and shale gas. Higher energy prices tend to trigger or prolong economic recessions, and may even force changes in an economy’s structure, such as the total number or average size of firms (Mitchell & Mulherin, 1996). Economic recession leads to a decrease in consumption and ultimately results in excess capacity in an economy. M&A has been widely used to modify overall capacity by changing economic structures (Andrade, Mitchell, & Stafford, 2001).
Consequently, this study added energy price as a macro variable. Oil price was a proxy for energy price.

Finally, exports and imports were included in the macroeconomic dataset. These two variables combined indicated openness of an economy (Kamaly, 2007). Kamaly (2007) and Di Giovanni (2005) provided empirical evidence of the impact of economic openness on M&A activity. This study included the sum of seasonally-adjusted exports and imports measured in U.S. dollars to the macroeconomic set.

**Error Correction Model**

To identify appropriate macroeconomic determinants of restaurant M&A waves, this study compared three estimation models with different proxy variables for current economy: GDP, personal consumption expenditure (PCE) on foodservice and accommodation, and total GDP of Organisation for Economic Co-operation and Development (OECD) countries. These three comparable estimation models were newly developed using individual macroeconomic variables for model comparison. The results of the previous factor analysis indicated that macroeconomic variables were categorized into four-factor groups. Based on these results, four macroeconomic variables, one representing each of the four factors, were included in these models. In the first model, GDP represented for CA, yield spread (the difference between 10-year Treasury bond and 3-month Treasury bill) for CD, S&P500 for EO, and PPI for INF. In the second and third models, compatible industry-specific and global variables replaced GDP. PCE on foodservice and accommodation was included in the second model while OECD GDP was added to the third model.

The basic model was specified as follows:

\[
\ln DF_t = \beta_0 + \beta_1 \ln GDP_t (or \ ln PCE_t or \ ln OGD P_t) + \beta_2 SPR_t + \beta_3 \ln S&P_t + \beta_4 \ln PPI_t + \epsilon
\]
where $ln$ = logarithmical transformation, $DF_t$ = quarterly deal frequency of restaurant M&A deals, $GDP_t$ = quarterly GDP, $PCE_t$ = quarterly personal consumption expenditure on foodservice and accommodation, $OGDP_t$ = quarterly total GDP of OECD countries, $SPR_t$ = quarterly yield spread, $S&P_t$ = quarterly average of S&P 500, and $PPI_t$ = quarterly producer price index.

The relationship between variables may be spurious when the variables are non-stationary and under this condition unreliable inference can be made from OLS (Tang & Nair, 2002). Thus, this study employed the ADF test to check stationarity of the variables examined and found them to be stationary when first-differenced. Although statistical inferences with such stationary data in differenced form are reliable, the inferences are limited to short-term effects and researchers often fail to estimate long-term effects between variables (De Boef & Keele, 2008). Moreover, variables being stationary in the same order suggest that they may be cointegrated, which is described as a statistical property in which variables’ linear combination is stationary or (more generally) moves closely together (Dritsakis, 2004). When cointegration is present between variables, the variables have a long-term equilibrium relationship. Thus, to cover the short and long-term effects of macroeconomic variables on restaurant M&A waves and avoid spurious relationships, this study adopted an error correction model (ECM) based on autoregressive distributed lag (ADL) approach to cointegration. ECM also shows deviations of short-term effects from the long-term equilibrium relationship and how the deviations are modified moving toward long-term equilibrium over time. Multicollinearity problems can be addressed in ECM. The appropriate lag length was determined by Bayesian information criterion (BIC) as well as AIC. The basic model were converted into ECM models with ADL:
\[ \Delta \ln DF_t = \alpha + \beta_1 \Delta \ln GDP_t \ (or \ \Delta \ln PCE_t \ or \ \Delta \ln OGD_P_t) + \beta_2 \Delta SPR_t + \beta_3 \Delta \ln S&P_t + \beta_4 \Delta \ln PPI_t + \gamma ECT_{t-1} + \epsilon \]

where \( ECT_{t-1} = \ln DF_{t-1} - \gamma_1 \ln GDP_{t-1} \ (or \ \ln PCE_t \ or \ \ln OGD_P_t) - \gamma_2 \ln SPR_{t-1} - \gamma_3 \ln S&P_{t-1} - \gamma_4 \ln PPI_{t-1} \). \( ECT_{t-1} \) is an error correction term which shows speed of modification of short-term deviations. The long-term equilibrium relationship can also be derived from the term. \( \beta_1, \beta_2, \beta_3, \) and \( \beta_4 \) represent short-term effects of economic variables on restaurant M&A waves, while \( \gamma_1, \gamma_2, \gamma_3, \) and \( \gamma_4 \) represent long-term relationships.

**Data Collection**

This study obtained restaurant M&A data from SDC Platinum’s Mergers and Acquisitions database. The sample contained all restaurant M&A deals in the United States from 1981 to 2013. This included all U.S. restaurant firms, as defined by Standard Industry Classification (SIC) code 5812, regardless of whether they were public or private, who were involved in M&A deals. SIC code 5812 is the U.S. Department of Labor’s four-digit code for eating places described as “establishments primarily engaged in the retail sale of prepared food and drinks for on-premise or immediate consumption” (U.S. Department of Labor, 2015). This category also includes “caterers and industrial and institutional food service establishments” (U.S. Department of Labor, 2015). This study identified 2,766 restaurant M&A deals involving foodservice business coded 5812, and excluded from the sample 1,351 deals whose deal values were not known. A total of 1,415 completed M&A deals were identified as usable data. 1,332 deals between 1981 and 2010 were used for M&A wave identification and ADL estimation and 1,415 deals between 1981 and 2013 for ECM estimation. The quarterly frequency and value of the M&A deals were computed.
Table 3.1

*Description of macroeconomic variables*

<table>
<thead>
<tr>
<th>Symbol</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>CPI</td>
<td>Seasonally adjusted consumer price index, 1982-1984 = 100</td>
</tr>
<tr>
<td>CU</td>
<td>Capacity utilization (%)</td>
</tr>
<tr>
<td>DJI</td>
<td>Dow Jones Index</td>
</tr>
<tr>
<td>EMP</td>
<td>Seasonally adjusted total number of employees in millions</td>
</tr>
<tr>
<td>EX</td>
<td>Seasonally adjusted export in US$ billions</td>
</tr>
<tr>
<td>FEDS</td>
<td>Federal Funds rate</td>
</tr>
<tr>
<td>OIL</td>
<td>Oil price</td>
</tr>
<tr>
<td>GDP</td>
<td>Seasonally adjusted gross domestic production in US$ billions</td>
</tr>
<tr>
<td>IM</td>
<td>Seasonally adjusted import in US$ billions</td>
</tr>
<tr>
<td>IP</td>
<td>Seasonally adjusted industrial production index, 2007 = 100</td>
</tr>
<tr>
<td>LTI</td>
<td>10-year Treasury bond rate</td>
</tr>
<tr>
<td>M1</td>
<td>Sum of currency, traveler's checks, demand deposits, and other checkable deposits in US$ billions, each seasonally adjusted separately</td>
</tr>
<tr>
<td>M2</td>
<td>Sum of savings deposits, small-denomination time deposits, retail money market mutual funds, and M1 in US$ billions, each seasonally adjusted separately</td>
</tr>
<tr>
<td>OGDP</td>
<td>Total GDP of OECD countries</td>
</tr>
<tr>
<td>PCE</td>
<td>Personal consumption expenditure on foodservice and accommodation</td>
</tr>
<tr>
<td>PPI</td>
<td>Producer price index, 1982 = 100</td>
</tr>
<tr>
<td>S&amp;P</td>
<td>Standard &amp; Poor’s 500 Index</td>
</tr>
<tr>
<td>SPR</td>
<td>Yield spread calculated as the difference between LTI and STI</td>
</tr>
<tr>
<td>STI</td>
<td>3-month Treasury-Bill rate</td>
</tr>
<tr>
<td>UEMP</td>
<td>Seasonally adjusted unemployment rate for all industries</td>
</tr>
</tbody>
</table>

The macroeconomic dataset for factor analysis consisted of 16 U.S. domestic macroeconomic variables. Three more variables were used to develop ECMs for model comparison. This study collected quarterly macroeconomic data from five different sources: the Center for Research in Security Prices (CRSP), the Federal Reserve Board (FRB), the OECD
statistics, the U.S. Department of Commerce, and the U.S. Department of Labor. Table 3.1 lists the macroeconomic variables with their descriptions.
References

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CHAPTER 4. WHAT DRIVES MERGERS AND ACQUISITIONS WAVES IN THE RESTAURANT INDUSTRY?

A manuscript to be submitted to Journal of Hospitality & Tourism Research

ABSTRACT

This study investigated the occurrence of mergers and acquisitions (M&A) waves in the restaurant industry. By comparing actual frequency of M&A deals with simulated randomly-generated deal frequency distributions, this study proved the presence of restaurant M&A waves. Macroeconomic determinants of the restaurant waves were then identified using factor analysis to extract underlying latent factors from 16 macroeconomic variables and a distributed lag model to investigate the effect of macroeconomic factors on the waves. Results showed that all factors (current activity, economic outlook, cost of debt, and inflation) significantly affected deal frequency, while current activity influenced only deal value. Theoretical and practical implications of the findings are presented.

Keywords: Mergers and acquisitions waves, macroeconomic determinants, restaurant industry, simulation

INTRODUCTION

In business, mergers and acquisitions (M&A) provides various benefits, including cost reduction, economies of scale, growth rate increase, financial stability, and profitability improvement (Gugler, Muller, & Yurtglu, 2003; Kanpp, Gart, & Chaudhry, 2006; Kiymaz, 2004; Park & Jang, 2011), thereby ultimately increasing shareholders’ value (Demirbag, Ng, & Tatoglu, 2007; Ma, Zhang, & Chowdhury, 2011). The significance of M&A in the restaurant industry has been growing along with the substantial increase of M&A activity for firm expansion and growth. According to the Securities Data Corporation (SDC) Merger and
Acquisition database, only 2 M&A deals valued at $248.53 million total were announced in the restaurant industry in 1980. However, the frequency and total value of restaurant M&A deals increased to 134 deals and $19.70 billion in 2007.

The drastic growth in restaurant M&A activity over the last three decades has undergone constant fluctuations. This uneven distribution of the aggregate level of M&A suggests the presence of an M&A wave, described as a remarkable increase in deal frequency and deal value during a certain period of time. M&A waves have been observed consistently at the industry, national, and global levels (Martynova & Rennboog, 2008). This indicates that M&A deals are more likely to take place under certain circumstances. In this respect, considerable scholarly efforts have been made to identify the determinants of M&A wave (Cook, 2007; Harford, 2005; Shleifer & Vishny, 2003).

One approach to identifying the determinants of M&A waves is to investigate the relationship between macroeconomic conditions and aggregate M&A activity. The macroeconomic approach to M&A wave analysis can reveal what and how macroeconomic conditions encourage M&A deals. Also, significant macroeconomic determinants of M&A waves can be used to identify the period of an M&A wave. According to Maksimovic, Phillips, and Yang (2013), M&A deals within the waves are value-added, while those outside the waves are less value-added or even value-destructive. This suggests that M&A deals cluster under certain economic conditions and that clustered M&A deals create more value than non-clustered ones. Therefore, identifying macroeconomic determinants allows restaurant firms to maximize the benefits of M&A deals by determining the appropriateness of economic circumstances and by predicting the optimal timing for an M&A deal. In addition, research on industry-level M&A wave becomes critical in understanding determinants of general M&A waves at a national level.
Recent finance studies (e.g., Andrade, Mitchell, & Stafford, 2001; Jovanovic & Rousseau, 2002) have highlighted that general M&A waves are initiated by the simultaneous clustering of M&A deals in several industries. Thus, to understand general M&A waves it is essential to first identify determinants of industry-level M&A waves and then find the common determinants across industries. However, to the best of the authors’ knowledge, there is no study that examines macroeconomic conditions driving M&A waves in the restaurant industry.

This study attempts to fill this gap in the restaurant literature by empirically investigating the macroeconomic determinants of restaurant M&A waves in the United States. Specifically, this study first examines the presence of restaurant M&A waves while identifying the periods of the M&A waves. Then, macroeconomic determinants of the restaurant M&A waves are investigated using factor analysis and time series techniques.

**LITERATURE REVIEW**

There have been six general M&A waves from since the 1890s (Alexandridis, Mavrovitis, & Travlos, 2011). The frequency and value of the first five M&A waves continued to grow compared to those of each previous wave. However, the sixth wave not only had smaller frequency and value than the previous fifth wave, but also showed that the premiums paid to target firms decreased due to the lack of confidence of acquirers in M&A deals (Alexandridis et al., 2011). While there has been an academic consensus regarding general M&A waves among finance and economics scholars, there is no shared understanding regarding the existence and period of industry-level M&A waves.

**Identification of Industry-level M&A Waves**

Many studies on M&A wave (e.g., Resende, 2008; Town, 1992) have investigated the presence of an M&A wave by focusing on general M&A activity from all industries. However,
since the 1990s, a growing body of literature has paid attention to industry-level M&A waves. Finance scholars (e.g., Adhern & Harford, 2014; Jensen, 1993; Rhodes-Kropf, Robinson, & Viswanathan, 2005) proposed and empirically proved that general M&A waves occur as a result of industry-level waves that simultaneously emerge in several industries. Accordingly, some studies (e.g., Mitchell & Mulherin, 1996; Harford, 2005) examined whether industry-level M&A wave exists and further identified the period of the waves. Mitchell and Mulherin (1996) studied M&A waves of 51 industries during the 1980s. The authors attempted to prove the occurrence of industry-level M&A waves by assessing whether the deal frequency between 1982 and 1989 varied across 51 industries. The results of a chi-square test rejected the null hypothesis that the variation of M&A activity in each industry is equal to that of all industries. They also found that more than 50% of the total M&A deals were clustered within the peak period of 24 consecutive months.

Harford (2005) used simulation technique for the identification of industry-level M&A waves to investigate the effect of industry circumstance on M&A waves. His study divided the study period into two ten-year periods: the 1980s and 1990s and focused 24-month peak period that M&A deals were concentrated in each decade based on the finding of Mitchell and Mulherin (1996). A total of 1,000 simulated random distributions of the actual deal frequency in each decade were generated in a given industry. The frequency of M&A deals in the highest 24-month period from each of 1,000 simulated draws was counted. These 1,000 of the highest deal frequencies formed a distribution for the 24-month peak period. The actual deal frequency in the highest 24-month period of each industry was compared with the simulated distribution for the 24-month peak period. When the actual highest frequency was higher than the 95th percentile of this simulated uniform distribution, the period could be identified as an M&A wave. The author
found 35 M&A waves in 28 industries including the lodging and the retail industries. The average deal frequency in a 24-month period outside of M&A waves was 8.5 deals while it was 34.3 deals within the waves.

Carow, Heron, and Saxton (2004) identified industry-level M&A waves in order to explore the difference in deal and firm characteristics between early and late M&As within M&A waves. The authors employed another way of identifying industry-level M&A waves to analyze the early-mover advantages in M&A deals. The first step for their study was to investigate whether industries experienced M&A waves between 1979 and 1998. They searched for the peak year in each industry, then found the start and last years surrounding the peak year. When an annual deal frequency became less than one-third of the peak frequency, the year was determined as the start or last years. The period from the start year to the peak year to the last year was defined as an M&A wave. This identification process discovered 14 M&A waves in 9 industries for 2 decades. This wave identification method is relatively simple to execute, but it may fail to find the waves because of non-existence of start, last, or both points.

**Relationship between Macroeconomic Conditions and M&A Waves**

Seminal work by Nelson (1959) first proposed the relationship between macroeconomic conditions and M&A waves. He examined the effects of stock prices and industrial production on aggregate U.S. M&A activity from 1895 to 1956. The findings from his study showed that wave movements in aggregate M&A activity were significantly positively related to changes in the stock market. Following Nelson’s (1959) study, a large body of literature in finance and economics has empirically supported the systematic effects of macroeconomic conditions on M&A waves (Finn & Hodgson, 2005).
The effect of stock prices on M&A wave has been extensively investigated in empirical studies (Benzing, 1993; Clarke & Ioannidis, 1996; Kamaly, 2007; Polonchek & Shushka, 1987). The expectations theory explains the relationship between stock prices and M&A wave. This theory claims that when economic outlook is optimistic, firms are likely to participate in M&A activity (Benzing, 1993). Firms expect markets in the optimistic economy to experience a lack of supply resulted from growing demand (Fama, 1981). M&A can be considered as a viable way for the firms to secure additional capacity if they desire to penetrate the undersupplied market. Expectations regarding future economy have typically been proxied by stock prices and a strong economic forecast has been empirically proven to be related to M&A waves (Benzing, 1991; Haque, Harnhirun, & Shapiro, 1995; Komlenovic, Mamun, & Mishra, 2011; Resende, 2008).

According to the capital market theory, M&A waves are influenced by interest rates. Because most firms tend to leverage their investment plans, reduction in external financing cost may encourage sizable corporate activities including M&A. Cost of debt is determined by interest rates. Therefore, low interest rates highly motivate M&A activity. Interest rates are also related to return on investment (ROI). When firms are considering an investment plan, they estimate expected ROI to decide whether to implement the plan. When the plan’s estimated ROI is higher than the expected return of management or investors, the plan is implemented. Interest rate is used to calculate the plan’s net present value (NPV) by discounting future cash inflows expected from the planned investment. The lower the interest rates, the higher the expected ROI. In sum, low interest rates lead to reduced financing costs and increased ROI, which facilitates M&A deals. Many M&A studies (e.g., Choi & Jeon, 2011; Corro, 2012; Melicher, Ledolter, & D’Atonio, 1983; Yagil, 1996) have found a significant effect of interest rate.
Current economic activity was also frequently examined as a potential determinant of M&A waves. Economic disturbance theory (Gort, 1969) describes the effect of current economic activity on M&A waves. According to the theory, M&A is attributable to the different valuation of a business between its existing shareholders and potential investors. The difference in the expected return between two parties increases when the current economy grows. As potential investors’ expected return from a business is higher than that of existing shareholders, the likelihood of M&A is greater. A primary measure of the current economic activity is Gross Domestic Product (GDP). Resende (2008) adopted the two-state Markov switching model to find out determinants of the U.K. M&A waves in the period of 1969 through 2004 and reported the significant effect of GDP. Choi and Jeon (2011) examined the effect of GDP on the wave movements in aggregate M&A activity between 1980 and 2004 in regard to deal frequency and deal value. The authors presented that GDP had a significant, positive effect on the deal frequency, but did not affect the deal value.

Industrial production is also a measure of current economic activity. However, while the impact of GDP on M&A waves was consistently significant, the effect of industrial production was inconclusive. Finn and Hodgson (2005) tested for the relationship between industrial production and M&A waves using the quarterly frequency of M&As in Australia during the period from 1972 to 1996. The findings reported the reciprocal relationship between these two variables. Industrial production had a significantly negative impact on M&A waves and, in turn, the waves positively affected industrial production, but the effect of the waves was not significant. Using the Granger causality test, Cook (2007) found evidence of a positive link between industrial production and the U.K. waves over the period 1975-2005. On the contrary, some studies stated the effect of industrial production on M&A waves was statistically
insignificant. Benzing (1991) investigated M&A waves from 1919 through 1979 and divided the study period into the two sub-periods. Industrial production had no significant effect on M&A waves for all periods: the entire period and two sub-periods. The recent study by Corrao (2012) examined macroeconomic determinants of general M&A waves and industry-level waves in ten industries. No significant effect of industrial production was found in the general M&A waves, but a significant effect was observed in several industries including the consumer staples, the healthcare, the industrials, the materials, and the utility industries.

The effect of capacity utilization on M&A waves has often been explored. There are two contradictory explanations regarding the relationship between capacity utilization and M&A waves. One explanation argued by neoclassical researchers is that M&A occurs to modify excess capacity led by rapid technological, economic, and regulation changes (Jensen, 1993). The other is that firms use M&A to gain operating capacity immediately to prepare for an optimistic future economy (Komlenovic et al., 2011). However, empirical evidence by Beckettii (1986) and Komlenovic et al. (2011) has shown the positive effect of capacity utilization supporting the latter explanation.

In addition to the macroeconomic conditions mentioned above, whose effects on M&A waves are supported by theories, other macroeconomic conditions were examined to identify economic forces that drive M&A waves. Those variables include unemployment rate (Benzing, 1991, 1993), liquidity (Resende, 2008), inflation measured by producer price index (PPI) (Golbe & White, 1988), export/import (Kamaly, 2007), and oil price (Polonchek & Sushka, 1987). Benzing (1991, 1993) investigated the effects of unemployment rate, arguing that as an economy becomes healthier the unemployment rate drops and M&A deals become more likely. These studies found that unemployment rate has a significant negative effect on M&A waves. In the
restaurant context, employment-related variables including unemployment rate may be more influential in that they are directly associated with household income (Diprete & McManus, 2000) which significantly affects restaurant business (Denizci, 2007). The relationship between M&A waves and liquidity can be understood in terms of opportunity cost. As the money supply grows, the opportunity cost of cash declines (Fishman, 1989). As a result, cash is preferred over alternative sources of financing for investment activities such as M&A (Resende, 2008). Thus, liquidity plays an important role in increasing M&A deals using cash payment. Abundant liquidity is viewed as the main reason for the sixth M&A wave (Alexandridis et al., 2011). In this vein, it is argued that sufficient liquidity is a necessary condition for industry-level M&A waves (Harford, 2005).

Inflation describes percentage changes in a general level of prices for goods and services. According to Panetta (2002), inflation affects the expected value of future cash flow. High inflation leads to increase in the expected cash flow and therefore facilitating investment activity. Thus, inflation is expected to have a positive relationship with M&A waves. Exports and imports combined can be used as an indicator of openness of an economy (Kamaly, 2007). The effect of economic openness on M&A waves was found to be significantly positive (Di Giovanni, 2005; Kamaly, 2007). Finally, energy-related commodities including oil and natural gas have been influential on an economy. Rising energy prices tend to precipitate economic downturn and structural changes in an economy such as changes in the number and size of firms (Mitchell & Mulherin, 1996). During economic downturn, the decline in demand for products and services leads to excess capacity within the economy. Excess capacity is removed until overall capacity reaches to new equilibrium in relation to demand, which brings about structural changes. M&A is widely utilized to adjust the level of capacity (Andrade et al., 2001).
Previous studies on determinants of M&A waves dominantly used pre-determined macroeconomic variables. Although several variables such as stock prices, interest rates, and GDP have a clear theoretical background, many other macroeconomic variables examined were subjectively selected based on various untested assumptions. This subjective variable selection process may make it difficult to model the true effect of macroeconomic variables on M&A waves because important variables may be omitted from the model. The omitted variables cause endogeneity problems resulting in over- or underestimated coefficients. Accordingly, this study examined a comprehensive set of macroeconomic variables to accurately capture their influence on M&A waves in the restaurant industry. However, it may not be easy to extract the unique effect of individual variables when a large number of macroeconomic variables are included in a model. Economic activities are complicatedly interrelated and thus, as the number of macroeconomic variables examined increases, more correlation among those variables is likely to occur causing multicollinearity (Cheng, 1995). Accordingly, exploratory factor analysis (EFA) was employed to address the multicollinearity problem in this study. This analysis uncovers underlying latent factors from a large set of explanatory variables without any theoretical support. Also, EFA can ease interpretation of the analytical results by reducing dimensions, but not changing the nature and character of the original variables.

**METHODOLOGY**

**Data**

The sample includes M&A deals between 1981 and 2010 in which U.S. restaurant firms falling under the Standard Industry Classification (SIC) code 5812 were involved. The study period (1981-2010) was determined based on Harford (2005) that attempted to identify industry-level M&A waves corresponding to general M&A waves in the 1980s and 1990s. Using the SDC
Merger and Acquisition database, this study first identified 2,512 completed restaurant M&A deals that were announced in the study period. Among them, the deals whose value were undisclosed were excluded from the sample. A total of 1,332 restaurant deals were retained for data analysis. The quarterly frequency and value of the M&A deals was calculated to assess restaurant M&A waves.

Table 4.1

*Description of macroeconomic variables*

<table>
<thead>
<tr>
<th>Symbol</th>
<th>Description</th>
<th>Database</th>
</tr>
</thead>
<tbody>
<tr>
<td>CPI</td>
<td>Seasonally adjusted consumer price index, 1982-84 = 100</td>
<td>DOL</td>
</tr>
<tr>
<td>CU</td>
<td>Capacity utilization (%)</td>
<td>FRB</td>
</tr>
<tr>
<td>DJI</td>
<td>Dow Jones Index</td>
<td>CRSP</td>
</tr>
<tr>
<td>EMP</td>
<td>Seasonally adjusted total number of employees in millions</td>
<td>DOL</td>
</tr>
<tr>
<td>EX/IM</td>
<td>Sum of seasonally adjusted export and import in billion dollars</td>
<td>DOC</td>
</tr>
<tr>
<td>FEDS</td>
<td>Federal Funds rate</td>
<td>CRSP</td>
</tr>
<tr>
<td>GAS</td>
<td>Gas price</td>
<td>DOL</td>
</tr>
<tr>
<td>GDP</td>
<td>Seasonally adjusted Gross Domestic Production in billion dollars</td>
<td>DOC</td>
</tr>
<tr>
<td>IP</td>
<td>Seasonally adjusted industrial production index, 2007 = 100</td>
<td>FRB</td>
</tr>
<tr>
<td>LTI</td>
<td>10-year treasury-bond rate</td>
<td>CRSP</td>
</tr>
<tr>
<td>M1</td>
<td>Sum of currency, traveler's checks, demand deposits, and other checkable deposits in billion dollars, each seasonally adjusted separately</td>
<td>FRB</td>
</tr>
<tr>
<td>M2</td>
<td>Sum of savings deposits, small-denomination time deposits, retail money market mutual funds, and M1 in billion dollars, each seasonally adjusted separately</td>
<td>FRB</td>
</tr>
<tr>
<td>PPI</td>
<td>Producer price index, 1982 = 100</td>
<td>DOL</td>
</tr>
<tr>
<td>S&amp;P</td>
<td>Standard &amp; Poor’s 500 Index</td>
<td>CRSP</td>
</tr>
<tr>
<td>STI</td>
<td>3-month treasury-bill rate</td>
<td>CRSP</td>
</tr>
<tr>
<td>UEMP</td>
<td>Seasonally adjusted unemployment rate in all industries</td>
<td>DOL</td>
</tr>
</tbody>
</table>
The macroeconomic dataset examined includes 16 U.S. domestic macroeconomic variables. The quarterly data on the macroeconomic variables were collected from the Center for Research in Security Prices (CRSP), Federal Reserve Board (FRB), U.S. Department of Commerce (DOC), and U.S. Department of Labor (DOL). Table 4.1 shows the macroeconomic variables and their definition.

Identification of M&A Waves in the Restaurant Industry

Based on Harford’s (2005) method, this study tested whether restaurant M&A deals occur by chance or in waves. The study period was divided into three sub-periods: the 1980s, 1990s, and 2000s. As shown in Figure 4.1, each decade appeared to have distinct restaurant M&A waves which corresponded with the general M&A waves in all industries, one of which has occurred every decade since the 1980s. The deal frequency for each decade was, in chronological order, 323, 654, and 355. This study simulated 1,000 distributions of the actual deal frequency for each decade. In the simulation, it was assumed that the probability of assigning each M&A deal to a quarter in a decade was the same (1/40). Accordingly, the simulated distributions had a random process.

Figure 4.1. Restaurant M&A deals, 1981-2010
Next, this study calculated the deal frequency in the highest two-year period from each simulated draw to develop a distribution of the two-year peak period. Then, to investigate the presence of restaurant M&A waves in each decade, this simulated uniform two-year peak distribution was compared with the actual deal frequency. When the actual frequency in any consecutive two-year period of a decade (e.g., first quarter through eighth quarter or second quarter through ninth quarter) exceeded the 95th percentile of the simulated two-year peak distribution, the two-year period was considered as an M&A wave. The results from the comparison showed that there existed one restaurant M&A wave for each decade. Additionally, this study used the Kolmogorov-Smirnov (K-S) test to confirm the presence of the restaurant M&A waves identified by Harford’s (2005) method. The results showed the significant difference between the distribution of actual two-year restaurant M&A frequency and the simulated randomly-generated distributions of the actual two-year frequency. Harford’s (2005) simulation method and the K-S test provided empirical evidence of restaurant M&A waves and therefore, the rationale for the further study on macroeconomic determinants of the restaurant waves was supported.

**Exploratory Factor Analysis**

This study employed EFA to address multicollinearity problem by discovering underlying latent factors from 16 macroeconomic variables. Because the macroeconomic variables are all time series data, they may be non-stationary. This non-stationarity may lead to the violation of Independent and Identically Distributed (IID) assumption required in factor analysis (Gilbert & Meijer, 2005). This study used the Augmented Dickey-Fuller (ADF) test to check the presence of a unit root in each macroeconomic variable indicating non-stationarity. The statistical results showed the macroeconomic variables except the interest rate variables of
FEDS, LTI, and STI had a unit root. These macroeconomic variables having a unit root were taken as the first difference to avoid the violation of IID assumption. Also, logarithm transformation was applied to both the first-differenced variables and interest rate variables to make them more normally-distributed and equally-variant.

After transforming the macroeconomic variables, this study conducted EFA using Principal Axis Factoring method and Direct Oblimin method, a non-orthogonal rotation. The number of factors was determined by Kaiser’s Criterion and scree plot, and four latent factors were extracted. Considering the characteristics of macroeconomic variables with high factor loadings in each latent factor, this study named those factors as follows: Factor 1 Current Activity (CA), Factor 2 Cost of Debt (CD), Factor 3 Economic Outlook (EO), and Factor 4 Inflation (INF).

**Distributed Lag Model**

Two distributed lag models were developed to explore the relationship between the macroeconomic factors extracted and restaurant M&A waves. These models allowed the investigation of short and long-term effects of macroeconomic factors. In order to determine the length of lag, this study compared Akaike Information Criterion (AIC) of different lag models following the suggestion of Pagano and Hartley (1981). The comparison results indicated that four-lag models were the best fit to the sample. Dependent variables were the quarterly deal frequency and deal value. The Durbin-Watson (D-W) test was used to detect whether there was serial correlation in the models. D-W statistics indicated that the residuals in both models were serially correlated. Therefore, to control for the effect of past aggregate M&A activity on present M&A activity, Prais-Winsten estimation was employed for the distributed lag models based on
the approach of Hansen and Huang (1997). In addition, dummy variables were used to control
for seasonality. The estimated two models are specified as follows:

\[
DF_t = \beta_0 + \sum_{i=1}^{4} \beta_i MACRO_F_{i,t-j} + \sum_{k=1}^{3} QUARTER_k
\] (Model 1)

\[
DV_t = \beta_0 + \sum_{i=1}^{4} \sum_{j=0}^{4} \beta_i MACRO_F_{i,t-j} + \sum_{k=1}^{3} QUARTER_k
\] (Model 2)

where \(DF_t\) = deal frequency of restaurant M&As at time \(t\); \(DV_t\) = logarithmically-transformed
deal value of restaurant M&As at time \(t\); \(MACRO_F_{i,t}\) = four macroeconomic factors at time \(t\)
including \(CA, CD, EO,\) and \(INF\); and \(QUARTER_k\) = dummy variable for the first, second , and
third quarter of a year.

**RESULTS**

**Identification of Restaurant M&A Wave**

Table 4.2 provides the results from the investigation of the presence of restaurant M&A
waves. According to the simulation analysis, one restaurant wave occurred for each decade,
which corresponded to the general M&A wave pattern. Specifically, the periods between the
third quarter 1987 and the second quarter 1990, between the fourth quarter 1994 and the first
quarter 1999, and between the first quarter 2006 and the fourth quarter 2008 were identified as
restaurant M&A waves. The average wave period was 14 quarters and the longest period was 18
quarters in the 1990s when restaurant M&A activity was the most vigorous (654 M&A deals).
The deal frequency within each wave accounted for 41.40%, 59.94%, and 39.43%, respectively,
of the total deals in each decade. Average deal frequency within the waves was at least 52%
more than that in non-wave periods.
Table 4.2

Results of restaurant M&A wave identification

<table>
<thead>
<tr>
<th></th>
<th>1980s</th>
<th>1990s</th>
<th>2000s</th>
</tr>
</thead>
<tbody>
<tr>
<td>Restaurant M&amp;A wave</td>
<td>3Q 1987 to 2Q 1990 (12 quarters)</td>
<td>4Q 1994 to 1Q 1999 (18 quarters)</td>
<td>1Q 2006 to 4Q 2008 (12 quarters)</td>
</tr>
<tr>
<td>M&amp;A within wave</td>
<td>134 / 323 (41.40%)</td>
<td>392 / 654 (59.94%)</td>
<td>161 / 355 (39.43%)</td>
</tr>
<tr>
<td>Avg. M&amp;A within wave</td>
<td>11.17/Q</td>
<td>21.78/Q</td>
<td>11.67/Q</td>
</tr>
<tr>
<td>Avg. M&amp;A out of wave</td>
<td>6.75/Q</td>
<td>11.91/Q</td>
<td>7.68/Q</td>
</tr>
<tr>
<td>K-S statistic</td>
<td>0.315*** (p=.003)</td>
<td>0.355*** (p&lt;.001)</td>
<td>0.258** (p=.027)</td>
</tr>
</tbody>
</table>

Note: Q = quarter. * 0.1, ** 0.05, and *** 0.01

K-S test results indicated p-values for all three decades were less than 0.05 rejecting the null hypothesis that the cumulative distribution function of the actual two-year restaurant M&A frequency is equal to the simulated distributions of the two-year restaurant deal frequency.

Figure 4.2 presents the actual and simulated distribution functions of the two-year restaurant deal frequency and the simulated distribution function for the two-year peak frequency in the 1990s. The actual and simulated CDFs of the two-year restaurant deal frequency are shown in Figure 4.3.
Figure 4.2. Distribution Functions of Two-year Restaurant M&A Frequency in the 1990s

Figure 4.3. CDFs of Two-year Restaurant M&A Frequency in the 1990s
Determination of Macroeconomic Factors

Table 4.3 presents descriptive results of the macroeconomic variables. During 20 years of the study period, import exceeds export on average and the sum of these two variables has increased over three times. In the same period, stock markets have increased over nine times and GDP over four times, while interest rates such as LTI and FEDS have plunged from 12-16% to below 0.2%.

Table 4.3

Descriptive statistics of macroeconomic variables

<table>
<thead>
<tr>
<th>Variable</th>
<th>Mean</th>
<th>SD</th>
<th>First Quarter</th>
<th>Last Quarter</th>
</tr>
</thead>
<tbody>
<tr>
<td>CPI</td>
<td>153.91</td>
<td>38.54</td>
<td>87.93</td>
<td>219.63</td>
</tr>
<tr>
<td>CU</td>
<td>79.54</td>
<td>3.88</td>
<td>80.32</td>
<td>75.38</td>
</tr>
<tr>
<td>DJI</td>
<td>6,111.83</td>
<td>3,778.20</td>
<td>1,005.76</td>
<td>11,573.49</td>
</tr>
<tr>
<td>EMP</td>
<td>116.87</td>
<td>15.46</td>
<td>91.11</td>
<td>130.28</td>
</tr>
<tr>
<td>EX/IM</td>
<td>489.97</td>
<td>290.05</td>
<td>152.37</td>
<td>1,096.00</td>
</tr>
<tr>
<td>FEDS</td>
<td>5.58</td>
<td>3.62</td>
<td>16.57</td>
<td>0.19</td>
</tr>
<tr>
<td>GAS</td>
<td>1.56</td>
<td>0.66</td>
<td>1.34</td>
<td>2.92</td>
</tr>
<tr>
<td>GDP</td>
<td>8,270.77</td>
<td>8,288.84</td>
<td>3,051.40</td>
<td>14,755.00</td>
</tr>
<tr>
<td>IM</td>
<td>277.77</td>
<td>172.21</td>
<td>78.36</td>
<td>607.98</td>
</tr>
<tr>
<td>LTI</td>
<td>6.96</td>
<td>2.92</td>
<td>12.96</td>
<td>2.83</td>
</tr>
<tr>
<td>M1</td>
<td>1,027.53</td>
<td>342.46</td>
<td>415.03</td>
<td>1,813.13</td>
</tr>
<tr>
<td>M2</td>
<td>4,380.00</td>
<td>1,974.59</td>
<td>1,620.73</td>
<td>8,727.67</td>
</tr>
<tr>
<td>PPI</td>
<td>129.08</td>
<td>26.04</td>
<td>96.1</td>
<td>188</td>
</tr>
<tr>
<td>S&amp;P</td>
<td>717.49</td>
<td>457.70</td>
<td>136.00</td>
<td>1,257.64</td>
</tr>
<tr>
<td>STI</td>
<td>5.03</td>
<td>3.13</td>
<td>13.36</td>
<td>0.14</td>
</tr>
<tr>
<td>UEMP</td>
<td>6.27</td>
<td>1.65</td>
<td>7.43</td>
<td>9.57</td>
</tr>
</tbody>
</table>

This study used EFA to determine underlying dimensions of 16 macroeconomic variables by analyzing their correlation patterns. Bartlett’s test of sphericity and the Kaiser–Meyer–Olkin (KMO) measure of sampling adequacy were employed to examine the appropriateness of the
macroeconomic data. The chi square value of 2,187.56 ($p<.001$) for Bartlett’s test and the KMO of 0.77 confirmed that the data was adequate for EFA. Principal Axis Factoring with Direct Oblimin rotation was applied to the data. According to Hair, Tatham, Anderson, and Black (1998), oblique rotation is better than orthogonal rotation under the assumption that factors are correlated with each other.

For the development of a parsimonious measure, macroeconomic variables were evaluated according to statistical criteria of Hatcher (1994), Hair et al. (1998), and Tabachnick, Fidell, and Osterlind (2001). Both measures of liquidity, M1 and M2, were deleted because of low communalities below .4. This study also discarded EX/IM due to its factor loadings greater than .4 on more than one factor and the small difference (less than .3) between the high cross-loadings. Without these deleted variables, this study returned to Bartlett’s test and a KMO measure, and their results were still robust. A four-factor model was determined based on Kaiser eigenvalue criterion and the scree plot test. The four-factor model explained 88.72% of the total variance of 13 variables. The factor loadings of macroeconomic variables were all more than .65. Four factors extracted and variables’ factor loadings are shown in Table 4.4.

Table 4.4

Results of EFA

<table>
<thead>
<tr>
<th>Variable</th>
<th>Current Activity</th>
<th>Cost of Debt</th>
<th>Economic Outlook</th>
<th>Inflation</th>
</tr>
</thead>
<tbody>
<tr>
<td>CU</td>
<td>.923</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>EM</td>
<td>.804</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>GDP</td>
<td>.699</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>IP</td>
<td>.964</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>UNEM</td>
<td>-.910</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>FEDS</td>
<td></td>
<td>.991</td>
<td></td>
<td></td>
</tr>
<tr>
<td>LTI</td>
<td></td>
<td>.817</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
### Table 4.4 (continued)

<table>
<thead>
<tr>
<th>Variable</th>
<th>Current Activity</th>
<th>Cost of Debt</th>
<th>Economic Outlook</th>
<th>Inflation</th>
</tr>
</thead>
<tbody>
<tr>
<td>STI</td>
<td>.941</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>DJI</td>
<td>.956</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>S&amp;P</td>
<td>.969</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>CPI</td>
<td></td>
<td>.770</td>
<td></td>
<td></td>
</tr>
<tr>
<td>GAS</td>
<td></td>
<td>.838</td>
<td></td>
<td></td>
</tr>
<tr>
<td>PPI</td>
<td></td>
<td>.907</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

| Eigenvalue | 5.199 | 2.540 | 1.936 | 1.859 |
| Variance explained | 39.99% | 19.54% | 14.89% | 14.30% |

### Relationship between Economic Conditions and Restaurant M&A Wave

This study established two distributed lag models to identify the macroeconomic determinants of M&A waves in the restaurant industry. Table 4.5 summarizes the results from the time-series analysis. Both models were serially correlated in that the D-W statistics were far below or above the critical value. Therefore, this study used Prais-Winsten estimator to address serial correlation. After Prais-Winsten procedure corrected the original models having serially correlated residuals, the transformed D-W statistics provided the sound results. In Model 1, using deal frequency as the dependent variable, there was no significant factor in the short term as shown in the coefficients at time t. In terms of lagged effect, the lagged CA at time t-4 was significantly positive on deal frequency at the 1% level ($\beta=3.042, p=.005$). $EO_{t-2}$ ($\beta=1.559, p=.022$) was found to be significant and $EO_{t-3}$ ($\beta=1.490, p=.060$) and $EO_{t-4}$ ($\beta=1.321, p=.065$) were marginally significant. These findings indicates previous general economic activity and previous stock market movements have a positive impact on current restaurant M&As. All lagged $INF$ factors had negative relationships to the deal frequency, but only one lagged...
relationship at time t-2 ($\beta=-1.115, p=.065$) was marginally significant. $EO$ ($\beta=4.498, p=.043$) had a significant the long-term effect on deal frequency that combined the short-term and all lagged effects. The long-term effect of $CD$ ($\beta=-2.111, p=.067$) was marginally significantly positive. It suggests that although interest rate and stock prices do not affect restaurant M&A activity immediately, the total effect of these factors over time is significant.

In Model 2, this study did not find any significant short-term effect on deal value. On the contrary, some significant lagged relationships between macroeconomic factors and deal value was found. The coefficient of $CA_{t-4}$ was marginally significantly positive ($\beta=0.436, p=.082$), indicating that previous general economic activity is closely related to the deal value of current restaurant M&As. $EO_{t-3}$ ($\beta=0.299, p<.057$) and $EO_{t-4}$ ($\beta=0.202, p<.081$) had a marginally significant coefficient. This implies that the current deal value is likely to increase three quarters after stock prices increase and that the positive lagged effect lasts by up to four quarters after the increase. The long-term effect of $EO$ ($\beta=0.646, p<.054$) was marginally significant. It indicates that one unit increase in stock prices result in 0.65% increase in the deal value.

Table 4.5

*Coefficients in distributed lag models*

<table>
<thead>
<tr>
<th></th>
<th>Model 1</th>
<th></th>
<th>Model 2</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>$\beta$</td>
<td>p-value</td>
<td>$\beta$</td>
<td>p-value</td>
</tr>
<tr>
<td><strong>Current Activity</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>T</td>
<td>-0.116</td>
<td>.921</td>
<td>-0.161</td>
<td>.495</td>
</tr>
<tr>
<td>t-1</td>
<td>-0.555</td>
<td>.694</td>
<td>-0.241</td>
<td>.410</td>
</tr>
<tr>
<td>t-2</td>
<td>-0.852</td>
<td>.522</td>
<td>0.261</td>
<td>.358</td>
</tr>
<tr>
<td>t-3</td>
<td>0.334</td>
<td>.778</td>
<td>-0.028</td>
<td>.919</td>
</tr>
<tr>
<td>t-4</td>
<td>3.042</td>
<td>.005***</td>
<td>0.436</td>
<td>.082*</td>
</tr>
<tr>
<td><strong>Short-term effect</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>-0.116</td>
<td>.921</td>
<td>-0.161</td>
<td>.495</td>
</tr>
<tr>
<td><strong>Long-term effect</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>1.854</td>
<td>.217</td>
<td>0.266</td>
<td>.326</td>
</tr>
<tr>
<td><strong>Cost of Debt</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>T</td>
<td>5.042</td>
<td>.212</td>
<td>0.128</td>
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<tr>
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<td>.829</td>
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Table 4.5 (continued)

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<tr>
<td></td>
<td>$\beta$</td>
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<tr>
<td>t-2</td>
<td>-2.540</td>
<td>.616</td>
</tr>
<tr>
<td>t-3</td>
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<td>t-4</td>
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<tr>
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**Economic Outlook**

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<tr>
<td>t</td>
<td>-0.189</td>
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<td>-0.071</td>
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<td>t-1</td>
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<td>t-2</td>
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<td>.065*</td>
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<td>.081*</td>
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**Inflation**

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<td>t-4</td>
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<tr>
<td>Long-term effect</td>
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<td>-0.129</td>
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**Seasonality**

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<td></td>
<td>-5.399</td>
<td>.234</td>
<td>-1.119</td>
<td>.220</td>
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**F-statistics**

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<td>2.010</td>
<td>.013**</td>
<td>4.740</td>
<td>.000***</td>
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**D-W:**

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<td>Original</td>
<td>1.203</td>
<td>1.488</td>
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<tr>
<td>Transformed</td>
<td>2.074</td>
<td>2.082</td>
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$R^2$

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<tr>
<td></td>
<td>.211</td>
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*** p<.01, ** p<.05, * p<.1

**DISCUSSION AND CONCLUSIONS**

Using factor analysis and time series techniques, this study investigated the macroeconomic determinants of restaurant M&A waves in the U.S. To provide rationale for this investigation on macroeconomic determinants, this study attempted to verify the presence of restaurant waves and identified three restaurant waves between 1981 and 2010. After confirming the presence of restaurant waves, this study proceeded to seek macroeconomic fundamentals on
the waves. First, using factor analysis, this study found underlying factors among 16 macroeconomic variables and determined a 4-factor solution for 13 variables. Then, restaurant M&A activity was estimated as a function of these macroeconomic factors.

There were several distinctive findings from the analysis. First, economic outlook has a significant effect on restaurant M&A waves. The long-term and lagged effects of economic outlook were found to be significantly positive. This finding supports the expectations theory that optimistic economic forecast encourages firms to involve in M&A activity. Previous literature has mainly shown the same positive relationship between M&A waves and economic outlook measured by stock prices (Benzing, 1991, 1993; Haque et al., 1995; Resende, 2008). Specifically, the positive lagged effect of economic outlook was significant on deal frequency and deal value. Combined with the long-term effect, it implies that increase in stock prices precedes to the occurrence of restaurant M&A waves and therefore, stock prices can be a significant predictor of the waves. On the contrary, the short-term effect of economic outlook was negative, but insignificant in both models. Even if this short-term effect was not significant, it is noted that the significant positive lagged effects became negative in the current term. This change in significance and direction can be explained in the context of deal price. The value of target firms is more likely to increase in strong stock market (Rhodes-Kropf & Viswanathan, 2005; Shleifer & Vishny, 2003). Higher value of target firms can force acquirers to resile from M&A deals or turn to more affordable targets, which reduce the aggregate frequency or value of M&A activity. Moreover, ROI reduced by increased target value may make it difficult for restaurant firms to conduct M&A. Given that the average profit margin for restaurant firms is quite narrow ranging from 1.8% to 3.5% of the total sales (National Restaurant Association, 2010), inappropriate or unaffordable investments may not only significantly deteriorate firm
profitability, but may also put their sustainability at risk. Because the final price offer is made in the later stage before M&A agreement, the negative effect of stock prices tends to be contemporaneous and thus may be able to offset the significantly positive long-term effect of stock prices in the short term.

Second, cost of debt has a significant effect on restaurant M&A waves. The significant effect was negative on deal frequency in the long-term. The finding is consistent with previous studies confirming the capital market theory (Becketti, 1986; Benzing, 1991; Choi & Jeon, 2011; Corrao, 2012). The results can be attributed to the preferred payment method in the restaurant industry. According to Chatfield, Chatfield, and Dalbor (2012), although two-thirds of the hospitality M&A deals using stock offer occurred in the restaurant industry, cash was the primary payment method in restaurant M&A deals (41.2% of all restaurant M&A deals). In respect to payment method, the empirical finding regarding cost of debt suggests that restaurant acquirers dominantly use debt financing directly associated with interest rates rather than internal cash fund to pay for their M&A deals. Indeed, restaurant firms having higher growth opportunities tend to use more and longer debt (Upneja & Dalbor, 2001). Moderate or excessive leverage is typical in fast food and family restaurant businesses (Gu, 1993).

Third, lagged macroeconomic factors are influential on restaurant M&A waves. In particular, lagged current activity and economic outlook were significant predictors of restaurant M&A waves. These findings indicate that in general, significant changes in macroeconomic conditions can be detected two to four quarters prior to M&A waves. According to Boone and Mulherin (2007), the M&A process prior to the public announcement of an M&A deal is called the Private Takeover Process (PTP), and it begins with top managers’ internal review of various strategic alternatives including M&A. Their study showed that PTP took eight to twelve months
regardless of that M&A agreement between acquirers and targets is made through auction or exclusive negotiation of two parties. It is noticeable that this duration of PTP corresponds to the time lags it takes for macroeconomic conditions to have an effect on restaurant M&A waves. This implies that from the initial stages of the M&A process, restaurant firms constantly consider changes in critical macroeconomic conditions to make more informed M&A decisions.

Combined with the findings on the lagged significant factors, it also suggests that changes in economic conditions lead restaurant firms to initiate an internal review of M&A possibilities as their main strategic plan.

Lastly, no significant macroeconomic factor influences deal frequency and deal value in the short term, while some factors have a significant long-term impact. From these findings, it is noted that restaurant firms can plan M&A from a long-term perspective. Economic conditions constantly change, forcing firms to take any action to respond to the changes. However, if the changes are not persistent, the corporate responses will be only temporarily effective. Thus, an immediate reaction to such changes may not be beneficial to firms in such a situation. The insignificant short-term relationship between macroeconomic factors and restaurant M&A waves signifies that temporary changes in the macroeconomy do not trigger clustering of restaurant M&A activity. Along with the significant long-term relationship, this suggests that restaurant firms are cautious in implementing M&A for taking advantage of or addressing the ever-changing temporary trend in economic conditions, but that when obvious trends are observed, firms actively respond to those changes. The significant long-term relationship also indicates that long-term economic trends that cause restaurant waves are traceable and therefore significant economic conditions can be used to predict restaurant M&A waves. Given that M&A deals in
non-wave periods tend to be unprofitable, identification of obvious economic trends can help a firm maximize synergistic gains from concurrent restaurant M&A deals.

The findings from this study have several contributions to academia and the restaurant industry. Academically, this study is an initial attempt to prove that M&A waves exist in the restaurant industry and investigate the determinants of the restaurant M&A waves. Growing importance of M&A as an effective growth strategy has led to a number of studies devoted to M&A in the hospitality industry. Research topics of previous hospitality studies on M&A include post-merger performance (Hsu & Jang, 2007), preferred payment type (Chatfield et al, 2012), and prediction of potential M&A targets (Kim & Arbel, 1998). However, little hospitality research has focused on M&A waves which have drawn a considerable attention in the general business sector. Consequently, M&A waves remain a fruitful area of research in the hospitality industry, especially the restaurant industry. In respect of method, this study extends Harford’s (2005) M&A wave identification method based on simulation by supplementally comparing the actual and simulated distributions of deal frequency using the K-S test. While the simulation method focuses on the comparison of peak points in the actual and simulated distributions, the K-S test investigated the overall equality of two distributions based their CDF. This study also extends the impact of macroeconomic conditions to industry-level M&A waves by applying the theories for general M&A waves to the restaurant industry. M&A wave studies on macroeconomic determinants have been conducted mainly focusing on general M&A waves. On the other hand, studies on industry-level waves put great emphasis on main causes of the waves such as industrial shocks and overvaluation of businesses. In addition, the restaurant industry was not an area of interest in the industry-level M&A wave studies. However, this study
identified macroeconomic determinants of M&A waves in the restaurant context demonstrating the applicability of general M&A wave theories to restaurant M&A waves.

Another contribution of this study is to provide practical and meaningful guidance for restaurant managers and executives who seek M&A. Restaurant managers need to take the findings of this study into account in formulating and implementing their M&A strategy to improve their operating performance and shareholders’ value. The findings show the macroeconomic factors to encourage restaurant M&A deals and the shifts in the important macroeconomic factors over M&A processes from internal review of strategic options to deal announcement. These macroeconomic factors should be checked continuously to determine whether economic conditions are appropriate for conducting M&A. Restaurant managers can also adjust the details of their M&A deals by looking into different macroeconomic factors at each step of the M&A process. Furthermore, managers are able to use the factors to predict a proper time for M&A.

The findings would be also beneficial for financial analysts and investors. The combination of the significant effect of four macroeconomic factors can help identify the period of restaurant M&A waves. Based on the unique impact of macroeconomy in the restaurant industry, financial analysts can develop a creative industrial forecast to show a feasible projection of restaurant M&A deals and investors and fund managers can find out the optimal time of investing in the restaurant industry.

LIMITATIONS AND SUGGESTIONS

Although this study identified the important macroeconomic factors driving restaurant M&A waves, it is not free from limitations. First, industry-level and firm-specific factors such as industry competition and growth, firm size, and market share were not controlled in this study.
Second, global macroeconomic factors were not considered. As the global market is integrated, more restaurant firms become multinational companies. Consequently, global macroeconomic conditions can be influential on M&A activity of those restaurant firms. Third, this study focused on the aggregate M&A activity without considering the profitability of the M&A deals. Future studies can expand understanding of M&A waves in the restaurant industry by addressing the limitations mentioned above. In addition, it would be interesting to examine the presence of cross-border restaurant M&A waves and their macroeconomic determinants.
REFERENCES


CHAPTER 5. EXAMINING THE RELATIONSHIP BETWEEN THE ECONOMIC ENVIRONMENT AND RESTAURANT MERGERS AND ACQUISITIONS ACTIVITIES: AN APPLICATION OF ERROR CORRECTION MODEL

A manuscript to be submitted to International Journal of Hospitality Management

Abstract

The purpose of this study was to investigate economic determinants of restaurant mergers and acquisitions (M&A) activity. An error correction model was used to explore the short- and long-term relationships between four economic variables and frequency of restaurant M&A deals. Results showed that restaurant M&A activity and economic variables had a long-term equilibrium relationship and that economic outlook had a significantly positive impact in the long term, while the effect of cost of debt was significantly negative in both the short and long term. The findings suggest that restaurant firms are more likely to implement M&A when they are optimistic about the future economy and use debt with low cost.

Keywords: Mergers and acquisitions, economic conditions, error correction model, cointegration

1. Introduction

Mergers and acquisitions (M&A) has been widely used as an important growth strategy in the restaurant industry for the past three decades (Park and Jang, 2011). According to the Securities Data Corporation’s (SDC) Merger and Acquisition database, the number of completed M&A deals in the restaurant industry was 534 in the 1980s and 898 in the 2000s. Over the same period, the total value of the M&A deals increased from US$34.9 billion to US$56.5 billion. Responding to this substantial increase in M&A deals, a growing body of literature has focused on M&A deals in the hospitality industry context, including the restaurant industry (Kim and Zheng, 2014). These studies (e.g., Chatfield et al., 2012; Oak et al., 2010; Sheel and Nagpal,
2000) primarily examined the wealth gains from M&A deals or the difference in gains according to various deal characteristics such as financing method.

Previous finance and economics studies (e.g., Golbe and White, 1993; Linn and Zhu, 1997; Resende, 2008) have empirically proved that M&A deals come in waves. Restaurant M&A deals seem also to cluster in some periods, as seen in Figure 5.1. These data suggest the existence of certain conditions that encourage M&A activity. Given the extent to which M&A brings about changes in market valuation and asset reallocation effects (Choi and Jeon, 2011; Finn and Hodgson, 2005), it is of great importance to understand the determinants of M&A activity. Moreover, M&A deals that take place in the clustering periods referred to as M&A waves are likely to create more market value than those in non-clustering periods (Maksimovic et al., 2013). Thus, the broaden understanding of the determinants can heighten the likelihood of maximizing synergistic effects by M&A. However, little research has focused on determinants of industry-level M&A activity, in particular restaurant M&A deals. To fill this research gap, this study attempts to identify economic determinants of restaurant M&A activity.

Figure 5.1. M&A deal frequency in the restaurant industry, 1981-2013.
In this investigation of the relationship between economic conditions and restaurant M&A deals, the following issues are considered: 1) short- and long-term effects of economic conditions on restaurant M&A activity, 2) non-stationarity of economic time-series variables, and 3) identifying an appropriate proxy for economic conditions. First, short- and long-term effects of economic conditions are explored. Given that the M&A process generally begins 8-12 months prior to public announcement (Boone and Mulherin, 2007), economic conditions may be a factor even in the early stages of the M&A process. Also, significant economic conditions may differ from the early stage to later stages. Thus, investigating both short- and long-term effects could provide reliable and meaningful results for academia and industry. Second, this study uses an error correction model (ECM) to deal with non-stationarity of economic time-series. Non-stationarity means that time-series’ means, variances, and covariances change over time (Wei, 2006). This unpredictability makes it difficult for such non-stationary time-series to be modelled or forecasted (Bowerman et al., 2005). Because it is highly likely that economic time-series are non-stationary, applying ordinary least square (OLS) to the series may produce spurious results (Granger and Newbold, 1974). ECM can solve this misspecification problem using cointegration among variables; this refers to a statistical property that although variables are not stationary, their linear regression is stationary. Moreover, short- and long-term effects can be estimated using ECM. Lastly, this study addresses the identification of an appropriate proxy for economic conditions that is more effective in explaining restaurant M&A activity. Three ECMs with different proxy variables are estimated to compare their model fit. Taken together, more complete estimation with dynamic specification would establish an understanding of industry-level M&A deals by providing robust evidence of economic conditions facilitating restaurant M&A activity.
2. Literature Review

2.1. Current Economy

Current economic performance is one important economic factor used to explain M&A activity. Melicher et al. (1983) argue that current economy reflects the expectations of future performance and thus a strong current economy shows optimism for the future economy. Based on this merger activity-economic prosperity theory, they used industrial production as a proxy for current economy, but failed to prove its significant effect on M&A activity. In addition to industrial production, gross domestic product (GDP), gross national product (GNP), and capacity utilization have been adopted as proxies for current economy. These variables have consistently shown a significant effect on M&A activity (Becketti, 1986; Choi and Jeon, 2011; Chung and Weston, 1982; Komlenovic et al., 2011; Resende, 2008; Steiner, 1975). Choi and Jeon (2011) investigated the effects of macroeconomic conditions on U.S. M&A activity between 1980 and 2004 using OLS and vector autoregression (VAR). Their OLS estimation results showed that GDP had a significantly positive impact on deal frequency and deal value. VAR estimation results showed that GDP was the most influential determinant in terms of deal frequency. By contrast, the significance of industrial production has been inconclusive (Benzing, 1991; Cook, 2007; Corrao, 2012) and the direction of the significant effect is inconsistent (Finn and Hodgson, 2005). Cook (2007) provided evidence of the positive effect of industrial production on U.K. M&A activity between 1975 and 2000. However, Benzing (1991) failed to find that industrial production had a significant effect. He explored the relationship between macroeconomic conditions and U.S. M&A activity between 1919 and 1979 dividing the study period into two sub-periods. The results showed that the effect of industrial production was not significant in either the entire period or the two sub-periods. Moreover, Finn and Hodgson (2005) found that
industrial production was significantly but negatively related to M&A activity in Australia during the period from 1972 to 1996.

This study used three proxy variables for current economy to develop three different models and compared those models to identify the most appropriate proxy for current economy. The proxy variables under consideration were GDP, personal consumption expenditure (PCE) on foodservice and accommodation, and total GDP of Organisation for Economic Co-operation and Development (OECD) countries. GDP was selected based on its consistent significance and frequent usage in previous studies (e.g., Choi and Jeon, 2011; Golbe and White, 1988; Resende, 2008) and the other two proxy variables were selected based on their ability to cover restaurant industry-specific characteristics. PCE on foodservice and accommodation is the component of GDP that directly shows the amount spent on dining out. As a proxy for global economy, OECD GDP may be more influential in restaurant firms with overseas units and may influence their M&A decisions further than the two domestic proxy variables mentioned above.

2.2. Economic Outlook

The expectations theory claims that optimistic expectations regarding the future economy increase M&A activity (Benzing, 1993; Kamaly, 2007). In a growing economy, supply shortages tend to result from increased demand (Fama, 1981). Thus, when future growth expectation is high, firms hasten to take advantage of the undersupplied state. M&A is a viable option that a firm can take to increase its available resources and capacity. Stock price has been frequently used to represent economic outlook and its relationship with M&A activity has been supported (Benzing, 1991; Haque et al., 1995; Kamaly, 2007).

Haque et al. (1995) examined the relationship between stock prices and M&A activity using Canadian M&A data for the period 1960 to 1989. Using the Granger causality test, they
found the relationship between stock prices and Canadian M&A activity to be significantly positive, which they suggest explains the dramatic increase in Canadian M&A activity in the 1980s. Kamaly (2007) tested the effect of stock prices on M&A activity in a developing country context, investigating M&A deals from 60 developing countries in the 1990s (1990-1999) using a dynamic panel model based on system-generalized method of moment (GMM) estimation. The results showed that stock prices significantly affected M&A activity in developing countries.

2.3. Cost of Debt

According to the capital market theory, M&A activity is influenced by cost of debt. Because sizable corporate investments tend to be leveraged and cost of debt determines the total financing cost, M&A decisions are likely to be sensitive to changes in cost of debt. Accordingly, low cost of debt spurs M&A activity by reducing the total cost for M&A deals. Many previous studies (e.g., Becketti, 1986; Choi and Jeon, 2011; Corrao, 2012) have examined the effect of cost of debt proxied by interest rates and consistently found its negative significance. Corro (2012) investigated the effect of cost of debt on general M&A activity in all industries and industry-level M&A activity in three specific industries using U.S. M&A data from between 1976 and 2011. The results showed that cost of debt was significantly, but negatively linked to general M&A activity and to M&A activity in consumer discretionary and energy industries. Komlenovic et al. (2011) investigated changes in the effect of cost of debt on M&A activity according to types of M&A. They developed panel regression models dividing the M&A data into two groups based on how closely the firms’ core businesses were related. Results indicated that cost of debt had a significantly negative effect on M&A deals regardless of whether or not the firms’ business areas were closely related, but the effect on unrelated M&A deals was higher than on related deals.
2.4. Inflation

Inflation indicates changes in the general level of prices. Prices are substantially influenced by changes in the existing economy structure (e.g., decrease in energy prices, increasing popularity of smartphones). Structural changes in an economy may create unexpected business opportunities increasing uncertainty. M&A is a useful instrument for firms seeking to exploit these opportunities. It is thus to be expected that higher inflation (representing greater economic change) produces more M&A deals. Based on this argument, Golbe and White (1988) examined the effect of inflation on U.S. M&A activity between 1940 and 1984. Producer price index (PPI) was added to the OLS estimation model as a proxy for inflation. Results showed that the coefficient of PPI was not significant with respect to deal frequency indicating when structural changes occurred in the U.S. economy, M&A was not preferably selected to tackle uncertain business circumstances.

2.5. Error Correction Model (ECM)

Because non-stationary data is likely to result in spurious regression, analysis using economic variables may not provide sound estimates (Song and Witt, 2000). To solve this problem, dynamic models have increasingly been adopted since the 1990s (Salleh et al., 2007). One of the popular models is ECM, introduced by Engle and Granger in 1987. Based on cointegrated relationships among economic variables of interest, ECM can show both the short-term relationship and long-term equilibrium, defined as “the state to which the (time) series converge over time” (De Boef and Keele, 2008). Long-term equilibrium can be viewed as a stable and unconditional relationship that variables achieve over time. ECM can also demonstrate that deviations from the long-term equilibrium occur in the short term and that these short-term deviations return to the long-term equilibrium over time through the process of self-
correction (Banerjee et al., 1990). Use of ECM is therefore justified when both long-term equilibrium and self-correction of short-term deviations are corroborated. In addition to the two advantages of ECM (avoiding the non-stationarity data problem and simultaneous estimation of both short- and long-term effects), ECM is less likely to suffer from multicollinearity because its independent variables are orthogonal (Syriopoulos, 1995).

Because the long-term equilibrium and deviation correction of ECM are useful in explaining organizational and human behavior, this method has also been widely used in social science fields including finance, political science, and tourism (De Boef and Keele, 2006; Song and Witt, 2000). These social science studies (e.g., Dritsakis, 2004; Li et al., 2004; Wang, 2009) have used ECM to estimate demand functions with the assumption that people or organizations rationally make their decisions using all information they have. However, irrational decision errors are often made by information asymmetry, thereby creating short-term deviations.

3. Methodology

3.1. Data

To identify determinants of restaurant M&A activity, this study modeled the relationship between economic variables and restaurant M&A deals from 1981 to 2013. Three models, each with different current economy proxies, were developed. Quarterly M&A numbers in the restaurant industry (SIC 5812) were obtained from the SDC Merger and Acquisition database. For this analysis, 1,415 deals with a total value of US$148.7 billion were identified. Quarterly data on GDP, PCE on food service and accommodation, OECD GDP, S&P 500 index, 10-year Treasury bond (T-bond), 3-month Treasury bill (T-bill), and producer price index (PPI) were collected from the Center for Research in Security Prices (CRSP), Federal Reserve Board (FRB), U.S. Bureau of Labor Statistics, and OECD Statistics. GDP, PCE on food service and
accommodation, and OECD GDP were used to represent current economy, while S&P 500 and PPI represented economic outlook and inflation, respectively. T-bond and T-bill yields were used to calculate yield spread (T-bond – T-bill) as a proxy for cost of debt. Table 5.1 provides the descriptive statistics of the economic variables

Table 5.1

<table>
<thead>
<tr>
<th>Variable</th>
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<tr>
<td>DF</td>
<td>9.62</td>
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<tr>
<td>GDP</td>
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<td>3,645.18</td>
</tr>
<tr>
<td>PCE</td>
<td>353.19</td>
<td>154.83</td>
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<tr>
<td>OGDP</td>
<td>27,996.10</td>
<td>6233.64</td>
</tr>
<tr>
<td>S&amp;P</td>
<td>717.49</td>
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<td>SPR</td>
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<tr>
<td>PPI</td>
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<td>26.04</td>
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</table>

Note: DF is M&A deal frequency. OGDP is OECD GDP in U.S. billion dollars. SPR is yield spread in percentage terms. Unit of GDP and PCE is U.S. million dollars.

3.2. Model Estimation

During analysis, the following equation was formulated as the basic model:

\[
\ln DF_t = \alpha + \omega_1 \ln GDP_t + \omega_2 \ln S&P_t + \omega_3 SPR_t + \omega_4 \ln PPI_t + \epsilon
\]

where \(\ln = \log\) transformation, \(DF_t = \) frequency of restaurant M&A deals in time \(t\), \(GDP_t = \) gross domestic product in time \(t\), \(S&P_t = \) average of Standard and Poor 500 index in time \(t\), \(SPR_t = \) yield spread in time \(t\), and \(PPI_t = \) producer price index in time \(t\).

Because estimation results from the basic model may be spurious due to the variables’ non-stationarity, a test for the presence of unit root was conducted using the Augmented Dickey-Fuller (ADF) test. The absolute values of the ADF statistics for all variables were less than the
critical value at α=0.01 indicating that the variables were not stationary in their levels. However, after taking their first-difference, the variables were found to be stationary. Table 5.2 presents the results of the ADF test.

<table>
<thead>
<tr>
<th>Variable</th>
<th>ADF Statistic</th>
<th>Differenced Variable</th>
<th>ADF Statistic</th>
</tr>
</thead>
<tbody>
<tr>
<td>lnDF</td>
<td>-2.266</td>
<td>lnΔDF</td>
<td>-7.867**</td>
</tr>
<tr>
<td>lnGDP</td>
<td>-2.055</td>
<td>lnΔGDP</td>
<td>-4.335**</td>
</tr>
<tr>
<td>lnPCE</td>
<td>-2.620</td>
<td>lnΔPCE</td>
<td>-4.152**</td>
</tr>
<tr>
<td>lnOGDP</td>
<td>-1.459</td>
<td>lnΔOGDP</td>
<td>-4.597**</td>
</tr>
<tr>
<td>lnS&amp;P</td>
<td>-1.525</td>
<td>lnΔS&amp;P</td>
<td>-4.889**</td>
</tr>
<tr>
<td>SPR</td>
<td>-1.738</td>
<td>ΔSPR</td>
<td>-4.681**</td>
</tr>
<tr>
<td>lnPPI</td>
<td>0.198</td>
<td>lnΔPPI</td>
<td>-5.359**</td>
</tr>
</tbody>
</table>

Note: ** denotes significance of ADF statistics at α=0.01.

The fact that the variables’ first differences proved stationary shows the possibility of their cointegration. Cointegrated variables have a long-term equilibrium relationship. Thus, to explore both short- and long-term relationships between variables, this study employed ECM based on autoregressive distributed lag (ADL) approach to cointegration developed by Pesaran and Shin (1998). Equivalence of ADL and ECM is a basis for ADL-ECM and means that the ADL model can be transformed into ECM. This study will demonstrate the transformation procedures with simple ADL(1,1):

\[
Y_t = \alpha + \beta_0 X_t + \beta_1 X_{t-1} + \phi_1 Y_{t-1} + \epsilon
\]  

By subtracting \(Y_{t-1}\) from both sides of Eq. 2, the ADL(1,1) can be represented as in Eq. 3:

\[
\Delta Y_t = \alpha + \beta_0 X_t + \beta_1 X_{t-1} - (1 - \phi_1) Y_{t-1} + \epsilon
\]  

where \(\Delta\) = first-difference operator and \(\Delta Y_t = Y_t - Y_{t-1}\). Replacing \(X_t\) with \((\Delta X_t + X_{t-1})\) in the right side of Eq. 3 yields:
\[ \Delta Y_t = \alpha + \beta_0 \Delta X_t + (\beta_0 + \beta_1) X_{t-1} - (1 - \varphi_1) Y_{t-1} + \epsilon \] 

(4)

Eq. 4 includes the error correction term (ECT) which shows the long-term equilibrium relationship. Thus, Eq. 4 can be reformulated as ECM:

\[ \Delta Y_t = \beta_0 \Delta X_t - (1 - \varphi_1) \{ Y_{t-1} - \frac{\alpha}{1 - \varphi_1} - \frac{(\beta_0 + \beta_1)}{(1 - \varphi_1)} X_{t-1} \} + \epsilon \]

or

\[ \Delta Y_t = \beta_0 \Delta X_t - (1 - \varphi_1) \{ Y_{t-1} - k_0 - k_1 X_{t-1} \} + \epsilon \] 

(5)

where \( k_0 = \frac{\alpha}{1 - \varphi_1} \) and \( k_1 = \frac{(\beta_0 + \beta_1)}{(1 - \varphi_1)} \). \( \{ Y_{t-1} - k_0 - k_1 X_{t-1} \} \) is ECT, which refers to a deviation (error) from the long-term equilibrium of \( X_t \) and \( Y_t \) when changes (or shocks) occur in \( X_t \). The deviation is not persistent and self-corrects over time, eventually returning to the equilibrium relationship (Song et al., 2003). The coefficient of ECT, \(- (1 - \varphi_1)\), is the correction rate at which the deviation made in the previous period is adjusted to the long-term equilibrium and therefore is expected to be negative. Over the long-term, \( X_t \) and \( Y_t \) have a perfect equilibrium relationship and thus the ECT becomes zero. Under this condition, the long-term model is derived as in Eq. 6:

\[ ECT_{t-1} = Y_{t-1} - k_0 - k_1 X_{t-1} = 0 \]

\[ Y_t = k_0 + k_1 X_t \] 

(6)

While the coefficient for \( \Delta X_t \) (\( \beta_0 \)) in ECM (Eq. 5) represents the short-term effect, the coefficient for \( X_t \) (\( k_1 \)) in the long-term model (Eq. 6) represents the long-term effect. Because the long-term model (Eq. 6) is derived from ECT, \( k_1 \) can be found in ECM (Eq. 5). This transformation can be applied to the general ADL(p,q) model.

Based on the transformation procedures, our basic model (Eq. 1) was first converted into general ADL form. Akaike information criterion (AIC) and Bayesian information criterion (BIC)
were used for lag selection for the ADL model. The ADL(1,1,1,1,1) representation of the basic model (Eq.1) was formulated as follows:

\[
\ln{DF}_t = \alpha + \gamma \ln{DF}_{t-1} + \beta_1 \ln{GDP}_t + \beta_2 \ln{GDP}_{t-1} + \beta_3 S&P_t + \beta_4 S&P_{t-1} + \\
\beta_5 \ln{SPR}_t + \beta_6 \ln{SPR}_{t-1} + \beta_7 \ln{PPI}_t + \beta_8 \ln{PPI}_{t-1} + \epsilon
\] (6)

Then, the ADL model (Eq. 6) was modified into ADL-ECM:

\[
\Delta\ln{DF}_t = \beta_1 \Delta\ln{GDP}_t + \beta_3 \Delta S&P_t + \beta_5 \Delta\ln{SPR}_t + \beta_7 \Delta\ln{PPI}_t + \lambda ECT_{t-1} + \epsilon \quad (7)
\]

\[
ECT_{t-1} = \ln{DF}_{t-1} - \theta - \varphi_1 \ln{GDP}_{t-1} - \varphi_2 S&P_{t-1} - \varphi_3 \ln{SPR}_{t-1} - \varphi_4 \ln{PPI}_{t-1}
\] (8)

where \( \lambda = -(1 - \gamma) \), \( \theta = \alpha/(1 - \gamma) \), \( \varphi_1 = (\beta_1 + \beta_2)/(1 - \gamma) \), \( \varphi_2 = (\beta_3 + \beta_4)/(1 - \gamma) \), \( \varphi_3 = (\beta_5 + \beta_6)/(1 - \gamma) \) and \( \varphi_4 = (\beta_7 + \beta_8)/(1 - \gamma) \).

The long-term (or cointegration) model was then derived from the ECT using ADL-ECM (Eq. 8):

\[
\ln{DF}_t = \theta + \varphi_1 \ln{GDP}_t + \varphi_2 S&P_t + \varphi_3 \ln{SPR}_t + \varphi_4 \ln{PPI}_t + \epsilon
\] (9)

This long-term model (Eq.9) was estimated based on the estimated ADL model (Eq.6). To test for cointegration between restaurant M&A activity and economic variables, the ADF test was performed for the residual of the long-term model (Eq.9). For the ADF test, both general ADF critical values and MacKinnon’s (1991) critical values were used to avoid false rejection of the null hypothesis of no cointegration (Song and Witt, 2000). After confirming the existence of the cointegration relationship, this study investigated the long-term effect of individual economic variables by calculating their standard error using the method developed by Bewley (1979). The short-term effect was examined using ADL-ECM (Eq. 7) based on the estimated long-term model (Eq. 9).
The ADL-ECM estimation process was then repeated for \( f(PCE, S&P, SPR, PPI) \) and \( f(OGDP, S&P, SPR, PPI) \). These models used PCE and OGDP as a proxy for current economy substituting GDP in the first model (Eq. 7). These three ECMs were compared to identify which economic variables were better at explaining restaurant M&A activity. This study employed AIC as a model comparison method which can be used for both nested and non-nested models.

4. Empirical Results

4.1. Cointegration Test

The estimates of our ADL models are given below:

\[
\ln DF_t = 4.457 + 0.295\ln DF_{t-1} - 1.966\ln GDP_t + 1.250\ln GDP_{t-1} + 0.296\ln S&P_t + 0.204\ln S&P_{t-1} - 0.149SPR_t + 0.042SPR_{t-1} - 0.182\ln PPI_t + 0.286\ln PPI_{t-1} \quad \text{(ADL Model 1)}
\]

\[
\ln DF_t = 2.590 + 0.278\ln DF_{t-1} - 4.892\ln PCE_t + 4.322\ln PCE_{t-1} + 0.285\ln S&P_t + 0.150\ln S&P_{t-1} - 0.159SPR_t + 0.046SPR_{t-1} - 0.139\ln PPI_t + 0.092\ln PPI_{t-1} \quad \text{(ADL Model 2)}
\]

\[
\ln DF_t = 42.791 + 0.268\ln DF_{t-1} - 5.577\ln OGDP_t + 2.698\ln OGDP_{t-1} + 0.385\ln S&P_t + 0.388\ln S&P_{t-1} - 0.147SPR_t + 0.047SPR_{t-1} + 0.620\ln PPI_t + 0.173\ln PPI_{t-1} \quad \text{(ADL Model 3)}
\]

Based on the estimated ADL Models, the long-term models derived from ECTs were estimated as follows:

\[
\ln DF_t = \frac{4.457}{(1-0.295)} + \frac{(-1.966+1.250)}{(1-0.295)}\ln GDP_t + \frac{(0.296+0.204)}{(1-0.295)}\ln S&P_t + \frac{(-0.149+0.042)}{(1-0.295)}SPR_t + \frac{(-0.182+0.286)}{(1-0.295)}\ln PPI_t + \varepsilon \quad \text{(Long-Term Model 1)}
\]
\[ \ln DF_t = \frac{2.590}{(1-0.278)} + \frac{(-4.892+4.322)}{(1-0.278)} \ln GDP_t + \frac{(0.285+0.150)}{(1-0.278)} \ln S&P_t + \frac{(-0.159+0.046)}{(1-0.278)} SPR_t + \frac{(-0.139+0.092)}{(1-0.278)} \ln PPI_t + \epsilon \]  
(Long-Term Model 2)

\[ \ln DF_t = \frac{42.791}{(1-0.268)} + \frac{(-5.577+2.698)}{(1-0.268)} \ln GDP_t + \frac{(0.385+0.388)}{(1-0.268)} \ln S&P_t + \frac{(-0.147+0.047)}{(1-0.268)} SPR_t + \frac{(0.620+0.173)}{(1-0.268)} \ln PPI_t + \epsilon \]  
(Long-Term Model 3)

The variables’ cointegration was examined using the ADF test. The ADF statistics for the residuals in all three Long-Term Models were significant at \( \alpha=0.01 \) and their MacKinnon’s \( p \)-values were also significant. These results showed that the residuals of these models were stationary, indicating that restaurant M&A activity and economic variables were cointegrated or had an equilibrium relationship in the long term. The cointegration test results are reported in Table 5.3.

<table>
<thead>
<tr>
<th>Cointegration test results</th>
<th>ADF statistic</th>
<th>MacKinnon p-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>( \epsilon ) Long Term 1</td>
<td>-5.787**</td>
<td>0.000</td>
</tr>
<tr>
<td>( \epsilon ) Long Term 2</td>
<td>-5.759**</td>
<td>0.000</td>
</tr>
<tr>
<td>( \epsilon ) Long Term 3</td>
<td>-6.035**</td>
<td>0.000</td>
</tr>
</tbody>
</table>

Note: ** denotes significance at 0.01.

### 4.2. Short- and Long-term Effects

Given the presence of the cointegration relationship, estimation for ECTs and the economic variables’ short- and long-term effect proceeded using ADL-ECMs. Table 5.4 reports the estimation results. We tested for serial correlation of ADL-ECMs using the serial correlation Lagrange Multiplier (LM) test and found no serial correlation problem. Coefficients of ECTs
were negative and significant. The result showed that the short-term deviation from the long-term equilibrium was corrected quickly. It re-validated the long-term equilibrium relationship.

The estimation results showed that GDP, PCE, OGDP, and PPI had no significant effect on restaurant M&A activity in the short term. The short-term effect of S&P was also insignificant in all three models. On the other hand, SPR had a significant negative short-term effect indicating that restaurant M&A activity immediately reacts to changes in yield spread. Since ECTs were equivalent to the Long-Term Models as seen in Eqs. 8 and 9, this study used the coefficients of economic variables in the Long-Term Models for individual long-term effect estimation. However, the Long-Term Models and ECTs did not directly provide the long-term coefficients’ standard error and therefore this study employed Bewley transformation to calculate their standard error. The results for the long-term effects showed that GDP, PCE, OGDP, and PPI were not significant, similar to the short-term effect results, while SPR and S&P were significant across the ADL-ECMs. It means that yield spread and stock prices significantly affect restaurant M&A activity over the long term. Specifically, as yield spread decreases, restaurant firms are more likely to make M&A deals. A 1% increase in stock prices leads to a 0.71 to 1.06% increase in restaurant M&A deals.

Table 5.4
Estimates of error correction models

<table>
<thead>
<tr>
<th></th>
<th>ADL-ECM 1</th>
<th>ADL-ECM 2</th>
<th>ADL-ECM 3</th>
</tr>
</thead>
<tbody>
<tr>
<td>lnΔGDP_t</td>
<td>-1.966 (-0.29)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>lnΔPCE_t</td>
<td></td>
<td>-4.892 (-0.74)</td>
<td></td>
</tr>
<tr>
<td>lnΔOGDP_t</td>
<td>0.296 (0.56)</td>
<td>0.285 (0.55)</td>
<td>0.385 (0.72)</td>
</tr>
<tr>
<td>lnΔS&amp;P_t</td>
<td>0.149* (-2.40)</td>
<td>0.159* (-2.55)</td>
<td>0.147* (-2.39)</td>
</tr>
<tr>
<td>ΔSPR_t</td>
<td>-0.182 (-0.94)</td>
<td>-0.139 (-0.06)</td>
<td>0.620 (0.24)</td>
</tr>
<tr>
<td>lnΔPPI_t</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>ECT_t-1</td>
<td>-0.705** (-8.37)</td>
<td>-0.722** (-8.46)</td>
<td>-0.732** (-8.62)</td>
</tr>
</tbody>
</table>
Table 5.4 (continued)

<table>
<thead>
<tr>
<th></th>
<th>ADL-ECM 1</th>
<th>ADL-ECM 2</th>
<th>ADL-ECM 3</th>
</tr>
</thead>
<tbody>
<tr>
<td>Long-term: GDP</td>
<td>-1.016 (-1.23)</td>
<td>-0.789 (-1.13)</td>
<td>-3.933 (-1.39)</td>
</tr>
<tr>
<td>PCE</td>
<td></td>
<td>-0.789 (-1.13)</td>
<td></td>
</tr>
<tr>
<td>OGDP</td>
<td>0.710* (2.26)</td>
<td>0.602* (2.47)</td>
<td>1.056** (3.49)</td>
</tr>
<tr>
<td>S&amp;P</td>
<td>-0.152** (-3.35)</td>
<td>-0.157** (-3.58)</td>
<td>-0.137** (-3.27)</td>
</tr>
<tr>
<td>SPR</td>
<td>0.148 (0.15)</td>
<td>-0.065 (-0.07)</td>
<td>1.082 (1.16)</td>
</tr>
<tr>
<td>PPI</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>R²</td>
<td>0.411</td>
<td>0.416</td>
<td>0.424</td>
</tr>
<tr>
<td>Serial correlation LM</td>
<td>2.071</td>
<td>2.515</td>
<td>1.701</td>
</tr>
<tr>
<td>AIC</td>
<td>155.212</td>
<td>154.264</td>
<td>152.627</td>
</tr>
<tr>
<td>BIC</td>
<td>183.003</td>
<td>182.055</td>
<td>180.419</td>
</tr>
</tbody>
</table>

Note: ADL-ECM 1 = \( f(GDP, S&P, SPR, PPI) \), ADL-ECM 2 = \( f(PCE, S&P, SPR, PPI) \), ADL-ECM 3 = \( f(OGDP, SPR, S&P, PPI) \). ** denotes significance at 0.01 and * at 0.05.

Finally, this study compared three ADL-ECMs with different proxies for current economy. As shown in the comparison results presented in Table 5.4, ADL-ECM 3 had larger values of \( R^2 \) and smaller AIC and BIC values than the other two models. The results imply that ADL-ECM 3 is not only the most effective at explaining the variance in restaurant M&A activity, but also has the smallest information loss when modeling M&A deals. Therefore, we conclude that ADL-ECM 3 including OGDP fits the data the best.

5. Discussion and Conclusions

This study conducted a series of analyses to identify economic determinants of M&A deals in the restaurant industry. First, we used cointegration to investigate whether the relationship between variables was in long-term equilibrium. Second, the short- and long-term effects of individual economic variables were examined using ADL-ECMs and a comparison of the three estimated ADL-ECMs was performed with respect to their model fit. The results showed the existence of a long-term equilibrium relationship between restaurant M&A activity and economic conditions, suggesting that rational M&A decisions using economic conditions...
have been made over the long term. It is also noticeable (as evidenced by the significant negative coefficient of ECTs) that restaurant firms make irrational decision errors occasionally in the short-term, but the errors converge to a long-term equilibrium over time. These irrational decision errors may be caused by managers’ poor decisions. According to the herding theory, some managers will simply follow the actions of the industry’s leading firms. In the case of M&A, successful M&A deals may lead other firms to become actively involved in M&A without careful analysis of their investment while failures in M&A drastically discourage subsequent M&A deals (Martynova and Renneboog, 2005). As a result of these irrational decisions, restaurant M&A activity deviates temporarily from the long-term equilibrium. This deviation is adjusted to achieve long-term equilibrium. For example, when S&P increases 1% in the ADL-ECM1, restaurant M&A activity increases 0.30% immediately. Because S&P and restaurant M&A activity have the long-term equilibrium relationship, any deviation between short- and long-term effects (0.71% - 0.30% = 0.41%) will be adjusted over future periods. According to the results of ADL-ECMs, more than 70% of the deviation in one period gets corrected in the next period.

Turning to the effect of individual economic conditions, this study confirms that the expectations theory can be applied to M&A activity in the restaurant industry. The significance of stock prices implies that when expecting an economic boom in the future, restaurant firms are more likely to use M&A to take advantage of the expected boom. Combined with the insignificance of the economic variables representing current economy, it is clear that economic outlook rather than current economy is the critical consideration in restaurant M&A decisions. On the other hand, significant evidence of yield spread supports the capital market theory, indicating that a decrease in the cost of debt leads to restaurant firms’ active involvement in
M&A. Given that cash offers are the major method of paying for M&A deals in the restaurant industry (Chatfield et al., 2012), the result suggests that debt has often been used to finance restaurant M&A deals and that improving earnings closely related to cost is a primary concern in such deals. In addition, the effects of economic variables on restaurant M&A deals can be used to predict when restaurant deals will be concentrated.

While the significant effect of economic outlook was long-term, the effect of cost of debt was both short- and long-term. Given that the M&A process—from the initial review of M&A by top management to deal announcement—generally takes eight to twelve months (Boone and Mulherin, 2007), the findings suggest that economic outlook and cost of debt lead restaurant firms to initially consider strategic M&A projects approximately one year before the M&A deal is announced. Further, firms modify these M&A projects in response to changes in economic conditions during this period. The significant short-term effect of cost of debt indicates that the decision to engage in an M&A deal depends on debt financing cost in the later stage of the M&A process. An increase in debt financing cost may result in a persistent deterioration in financial performance, in that long-term debt is likely to be used for large scale investment projects including M&A. Moreover, because the average profit margin of restaurants is low (1.8% - 3.5%) (National Restaurant Association, 2010), any increase in long-term interest cost may hurt corporate sustainability.

Comparing the three ADL-ECMs using different variables as proxies for current economy, this study finds that the ADL-ECM3 including OGDP is the best fit to the restaurant M&A data. Total GDP of OECD countries appears to be more important in determining restaurant M&A activity than the two domestic variables of GDP and PCE on food service and accommodation. This suggests that current economic conditions affecting restaurant M&A
activity are well captured by the global economic indicator. This phenomena may be attributable to the prevalence of global expansion in the restaurant industry. U.S. restaurant firms have adopted global expansion as an important strategy for avoiding intensive competition and high saturation in the domestic market (Hua and Upneja, 2007). This international expansion strategy is a significant industry trend, in particular for fast-food chain restaurants (Koh et al., 2009). Thus it is argued that global economic conditions may have more impact on restaurant business activities than domestic situations (Kim and Zheng, 2014). The model comparison results empirically support this argument.

This study has implications for research, theory, and practice. First, use of ADL-ECM allows us to estimate and test for both short- and long-term effects of economic conditions on restaurant M&A activity with non-stationary time-series data. This dynamic model generally gives valid and reliable estimates using a cointegrated relationship among variables (Banerjee et al., 1990; Song and Witt., 2000). ECM also reveals short-term deviations from the long-term equilibrium and illuminates the adjustment process by which the short-term disequilibrium returns to the equilibrium state over the long term (Li et al., 2006).

Second, the results of this study show that economic conditions can determine industry-level M&A activity. The effect of economic conditions has been investigated mainly in the context of general M&A activity in all industries while industry-level M&A studies have extensively focused on industrial shocks and stock overvaluation as main drivers of M&A deals. However, this study extends the theoretical frameworks for general M&A activity to industry-level M&A by identifying the economic determinants of restaurant M&A deals.

Finally, this study identifies important economic conditions that restaurant firms should carefully check when considering an M&A deal. Given that these effects are mostly long-term
and detectable, restaurant firms can modify their M&A plans to reflect changes in economic conditions and may be able to predict appropriate times for M&A deals, allowing the firms to increase their gains from M&A activity. Investment firms may also be able to project aggregate M&A activity using the economic determinants and therefore manage their portfolio more effectively by identifying the best time to invest in the restaurant industry. Finally, financial institutions could improve their performance by developing new financial instruments that help restaurant firms easily identify low-cost financing sources. Governments who seek to promote their country’s overall economy through increased M&A activity may wish to lower the benchmark interest rate or relax relevant regulations on financial markets to allow financial institutions to create innovative loan products.

6. Limitations and Future Research

This study has several limitations. First, this study used only the number of M&A deals as a measure of aggregate M&A activity. It would be valuable for future research to include the total value of M&A deals as another measure, or use deflators such as industry size to control for industry-specific effects. Second, this study did not explore what variables cause short-term deviation from the long-term equilibrium. It would be worthwhile to investigate what induces restaurant firms to make irrational decision errors. Such an investigation would demonstrate the transparency and effectiveness of the M&A decision making process. Finally, this study excluded cross-border M&A deals from its final sample and therefore the results may not fully capture the effect of economic conditions on restaurant M&A activity. Inclusion of cross-border M&A deals would enhance understanding of the total impact of economic conditions. Investigating cross-border M&A deals separately would also be worthwhile from an international business perspective. In addition, it would be interesting to investigate how the
effect of economic conditions changes according to deal characteristics such as payment type and deal size.
References


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CHAPTER 6. GENERAL CONCLUSION

This study proved that mergers and acquisitions (M&A) deals in the restaurant industry occur in wave patterns and then identified macroeconomic determinants of these M&A waves. For M&A wave verification, this study compared actual deal frequency with simulated random distributions. More specifically, this study investigated whether peak deal frequency and overall deal frequency could occur made by chance using Harford’s method and the Kolmogorov-Smirnov (K-S) test. After establishing the existence of restaurant M&A waves, this study investigated the short- and long-term effects of macroeconomic conditions on the M&A waves. This investigation addressed data stationarity, serial correlation, and multicollinearity using factor analysis, generalized linear squares (GLS), and econometric time series techniques such as a distributed lag (DL) model and error correction model (ECM). This chapter is organized into three sections: 1) summary of results, 2) discussions and implications, and 3) limitations and suggestions for future research.

Summary of Results

This study stands as a proof of the occurrence of restaurant M&A waves, showing that the restaurant industry experienced one M&A wave in each decade. Specifically, this study found that deal frequency in the periods of the third quarter 1987 through the second quarter 1990, the fourth quarter 1994 through the first quarter 1999, and the first quarter 2006 through the fourth quarter 2008 was significantly higher than the simulated random distributions and therefore identified these periods as restaurant M&A waves. Average deal frequency within the waves was 11.2, 21.8, and 11.7 per quarter respectively and these figures were at least 50% higher than deal frequency outside of the waves. The overall movements in actual deal frequency were also significantly different from random behavior.
This study also provides empirical evidence that restaurant M&A waves are determined by certain macroeconomic conditions. To explore the short- and long-term relationship between macroeconomic conditions and restaurant M&A waves, two different estimation methods were used. The first was a DL model based on Prais-Winsten estimation. Before estimating DL models, factor analysis was employed to identify macroeconomic latent factors for model specification. Sixteen macroeconomic variables were analyzed and three (M1, M2, and EX/IM) were deleted due to their low communalities or high cross-loadings. The remaining 13 variables were categorized into 4 factors: current activity (CA), cost of debt (CD), economic outlook (EO), and inflation (INF). Two DL models were then developed using two measures of restaurant M&A activity as dependent variables: deal frequency and deal value. Four-lag length for macroeconomic latent factors was selected by Akaike information criterion (AIC). Finally, Prais-Winsten estimation was applied to control for serial correlation detected in both models.

The estimation results showed that CA had a significantly positive lagged effect (t-4) on both deal frequency and deal value but no short- and long-term effects were found. The long-term effect of CD was found to be significant but negative on deal frequency. Surprisingly, there were no significant lagged and short-term effects. The results also revealed that EO had significant lagged and long-term effects on restaurant M&As. Specifically, the lagged effect of EO was significantly positive on deal frequency at t-2 through t-4, and on deal value at t-3 and t-4. Its long-term effect was found in both deal frequency and deal value. The effect of INF was relatively weaker than those of other macroeconomic factors, showing no short- or long-term effects on deal frequency and deal value. The sole significant effect was the lagged one on deal frequency at t-2.
The second model for the relationship between macroeconomic conditions and restaurant M&A activity was developed with ECM based on autoregressive distributed lag (ADL) approach. Following the results of factor analysis in the first model, four macroeconomic variables: GDP, Standard and Poor’s (S&P) 500 index, yield spread, and producer price index (PPI), were added to the model to represent four latent factors. To identify a proper proxy for current economy, this study developed two more ECMs using other proxy variables for current economy: personal consumption expenditure (PCE) on foodservice and accommodation and total GDP of Organisation for Economic Co-operation and Development (OECD) countries. GDP in the first ADL-ECM was replaced with these proxy variables in the other two ADL-ECMs and these three ADL-ECM models’ fits were compared. In all ADL-ECMs, deal frequency was used as a dependent variable.

Cointegration test results showed that cointegration existed among the variables examined, indicating that they had a long-term equilibrium relationship. This study therefore examined whether macroeconomic conditions influenced restaurant M&A activity in the short- and long-term. The results of three ECMs showed that PPI and all proxy variables for current economy (GDP, PCE, and OECD GDP) had no significant short- and long-term effects. On the other hand, yield spread significantly negatively affected deal frequency in both the short and long term. S&P had no significant short-term effect, but its long-term effect was significant. The coefficient for error correction term (ECT) was negative and significant as expected. Finally, the model comparison results reported that the ECM with OGDP had a better model fit to the data on deal frequency than other two ECMs.
Discussion and Implications

This study empirically proved that M&A deals occurred in waves in the restaurant industry. This finding highlights the important role of the restaurant industry in creating general M&A waves. To the best of our knowledge, this is the first attempt to demonstrate the existence of M&A waves in the restaurant context. Moreover, this study extends the M&A wave identification method by Harford (2005) by additionally comparing actual and simulated distributions of restaurant M&A deals. While the main focus of Harford’s simulation method was on the comparison of peak deal frequencies in actual and simulated distributions, this study compared their overall movements using the K-S test.

The existence of restaurant M&A waves suggests that M&A activity increases noticeably under certain circumstances. Identifying the circumstances is critical in improving M&A synergy. Accordingly, this study investigated the relationship between macroeconomic conditions and restaurant M&A waves. The findings show that economic outlook significantly influences restaurant M&A activity, supporting the expectations theory. It suggests that when restaurant firms expect a stronger future market, they are more likely to implement M&As to tackle this expected strong market. These findings are consistent with previous studies (e.g., Benzing, 1991, 1993; Haque, Hanhirun, & Shpiro, 1995; Resende, 2008). In addition, it is interesting to note that the significant positive effect of economic outlook turns negative in the short-term. This indicates that restaurant firms’ immediate reactions to stock price increases is negative. This change in effect direction may be related to deal price. In a bull market, target firms’ market value is likely to rise (Rhodes-Kropf & Viswanathan, 2005; Shleifer & Vishny, 2003), increasing their final price. Eventually, potential acquirers may not be able to afford an M&A deal and therefore they seek more affordable target firms or give up the idea of M&A
altogether. Moreover, because the increased deal price decreases return on investment (ROI) of M&A deals, it makes those deals less attractive.

This study also demonstrates that cost of debt is closely related to the occurrence of restaurant M&A waves, confirming the capital market theory. It means that low interest rates encourage M&A deals in the restaurant industry by reducing debt financing cost. Given that cash is widely used to pay for restaurant M&A deals, the findings suggest that debt instead of reserved cash is the primary funding source for restaurant M&A deals. In this line of thinking, Upneja and Dalbor (2001) argue that restaurant firms with high growth potential are highly leveraged with long-term debt.

These findings regarding economic outlook and cost of debt present that the expectations theory and capital market theory can be applied to the restaurant industry. Thus, this study expands knowledge about M&A waves by proving the applicability of theoretical frameworks for general M&A waves to industry-level M&A waves. Macroeconomic determinants have been identified primarily focusing on general M&A waves, while industry-level M&A wave research has investigated industrial shocks and overvalued stock prices as their potential determinants. Hence, this study’s findings help researchers improve their understanding of the impact of macroeconomic conditions on industry-level M&A waves.

The findings also indicate that the significant effects of macroeconomic conditions are mostly long-term and lagged, implying that identifiable changes in macroeconomic conditions occur prior to M&A waves and that restaurant firms would be wise to continuously check and reflect on such changes in their M&A decisions. According to Boone and Mulherin (2007), the M&A process known as a Private Takeover starts eight to twelve months prior to the deal announcement. This duration is the same as the time lags of the macroeconomic factors with
significant lagged effect, and suggests that the internal review of M&A as a strategic plan may be initiated due to specific changes in economic circumstances. In addition, given that all four macroeconomic conditions of interest have long-term or lagged effects while only cost of debt has a short-term effect, it is notable that restaurant M&As are planned and executed from a long-term perspective. In order words, restaurant firms use M&A as a response to obvious shifts in economic trends rather than as an immediate reaction to the ever-changing temporary economic situation.

Practical implications can be derived from the significant relationship between macroeconomic conditions and restaurant M&A waves. First, this study provides information about what and how economic conditions affect M&A decisions. Understanding this relationship becomes more important considering that deals occurring within M&A waves create more value than those occurring outside of the waves (Maksimovic, Phillips, & Yang, 2013). By using these important conditions for M&A wave forecast, restaurant firms can find an appropriate time for their M&A deals and adjust the details of a deal to maximize gains. Second, the findings can be useful to investors who can find the best time to invest in the restaurant industry and thereby more effectively manage their investment portfolio.

Limitations and Suggestions

There are several limitations in this study. First, this study did not thoroughly control for industry-level and firm-specific variables such as industry size, industry competition, firm size, and market share. Second, cross-border M&A deals referring to M&As between firms from different countries were excluded from the final sample for analysis. This exclusion might lead to a failure in capturing the total effect of macroeconomic conditions on restaurant M&A activity. Third, the estimation models used in this study did not consider deal characteristics that
might alter the effect of macroeconomic conditions. Addressing these limitations in future research would expand understanding of restaurant M&A waves. In addition, it would be worthwhile to investigate the macroeconomic determinants of cross-border M&A waves and identify causes of the difference between short- and long-term effects of macroeconomic conditions.
References


