Impacts of mass media coverage of the economy during normal times and recessions on the Index of Consumer Confidence using time series analysis and Granger causal analysis

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Impacts of mass media coverage of the economy during normal times and recessions on the Index of Consumer Confidence using time series analysis and Granger causal analysis

by

Lishan Su

A thesis submitted to the graduate faculty
in partial fulfillment of the requirements for the degree of

MASTER OF SCIENCE

Major: Journalism and Mass Communication

Program of Study Committee:
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Iowa State University
Ames, Iowa
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ABSTRACT

The level of consumer sentiment influences decision making of policy makers, and therefore it is important to examine if media have powerful impacts on consumer sentiment. Based on the theories of business cycles and second-level agenda-setting, this study applies Granger causal analysis and time series analysis to explore the causal relationships among economic reporting by media, consumer sentiment and the real state of the economy embodied in Business Week, the Index of Consumer Confidence (CCI) and the Standard & Poor’s 500 (S&P 500). The results indicate that interpretation by media have only limited effects on the level of consumer sentiment in general, and the real state of the economy plays a more important role in shaping consumer sentiment. However, during recessions and times of economic slowdowns, media have a more powerful effect on consumer sentiment though its impact is still smaller than the real state of the economy.
CHAPTER 1

INTRODUCTION AND STATEMENT OF THE PROBLEM

Over the past several years, policy makers have paid much attention to the American public’s mood, especially to consumers’ sentiments, in light of 9/11, a series of accounting scandals, the “war on terror,” and the persistent threats of recession. As a consequence, consumer sentiment surveys from reputable research centers are closely watched and widely reported. Several studies have found that there is a connection between public sentiment and the extent to which they consume goods and services (Doms & Morin, 2004). This is perhaps why this topic often receives wide media coverage. This study focuses on one such consumer sentiment survey conducted by the Conference Board Consumer Research Center, an independent economic research organization. It is widely known as the Index of Consumer Confidence or CCI.

The CCI is considered to be a principal indicator of how people feel about the United States economy. This indicator is issued monthly by the Conference Board, and is based on questionnaires mailed to a nationwide representative sample of 5,000 households, of which roughly 3,500 typically respond. Each month, a different panel of 5,000 households is surveyed. The CCI is based on people’s responses to five questions:

1. Respondents’ appraisal of current business conditions,
2. Respondents’ expectations regarding business conditions six months hence,
3. Respondents’ appraisal of the current employment conditions,
4. Respondents’ expectations regarding employment conditions six months hence, and
5. Respondents’ expectations regarding their total family income six months hence.
The Index of Consumer Confidence consists of the Present Situation Index (PSI), an indicator of consumers’ evaluations of current economic conditions, and the Expectations Index (EI), an indicator of consumers’ evaluations of economic conditions six months into the future (Hester & Gibson, 2003).

The level of consumer confidence predicts consumer spending which impacts the future trend of the economy (Boef & Kellstedt, 2004). The CCI is also a potent tool for economic forecasts. For instance, the CCI helped to predict the 1991 recession (Batchelor & Dua, 1998). Currently, the Federal Reserve Board looks at the CCI when determining interest rate changes, which subsequently affects stock market prices. The CCI also affects election outcomes and a variety of political behavior and attitudes such as macro-partisanship, presidential evaluations, public policy mood, congressional approval, and general trust in government (Boef & Kellstedt, 2004). Because of these, it is important to examine the media’s role in shaping consumer sentiment.

The CCI has always been an integral part of media reports about the economy. For instance, when the CCI plummeted to 86.6 in September 2005, Lynn Franco, Director of the Conference Board, interpreted the result as follows: “Hurricane Katrina, coupled with soaring gasoline prices and a less optimistic job outlook, has pushed consumer confidence to its lowest level in nearly two years.” Such interpretation, however, ignores the media’s role in pushing down the index. How did consumers receive information about Hurricane Katrina and the job market? What kind of information could so depress consumers’ sentiments? Did the information reflect the real state of the economy, or was it based on the media’s interpretation of the information to consumers? In short, does economic reporting by the media affect the Index of Consumer Confidence?
Previous research suggests that not all aspects of economics are known to consumers, and these aspects must be communicated to and interpreted for them by experts whose assessments are widely shared through the mass media (Boef & Kellstedt, 2004). While individual consumers are aware of their own fortunes and may have some sense of economic conditions more generally, they cannot directly experience all aspects of economic reality. Similarly, consumers cannot be aware of all events in Washington D.C. and other seats of political and economic power that might influence their economic future. Few have the inclination and the ability to digest the vast quantities of information that would allow them to develop evaluations based solely on economic conditions. Even when consumers are aware of objective economic conditions, the meanings and implications are seldom clear to them (Boef & Kellstedt, 2004). People generally rely more on the media for information about issues outside of their reach or personal experience, such as the current and future state of the economy (Hester & Gibson, 2003). Overall, the economic reality they perceive is mediated (Boef & Kellstedt, 2004).

A brief example illustrates this point. On September 12, 2005, Business Week reported that, “Throughout the summer, rising energy prices were the major topic of any discussion of the economy's future. Now, Hurricane Katrina has added her own stamp on the outlook for the second half. Residents of Louisiana, Alabama, and Mississippi are still tallying up the human and financial losses, as Katrina could shape up to be the costliest hurricane in U.S. history” (Cooper & Madigan, 2005). Without such analysis provided by the media, people may not even begin to know that Katrina was among the most devastating and costliest hurricanes in the nation’s recent past.
Only a few studies have investigated the complex relationships among news coverage of the economy, the real state of the economy, and the public’s perception of the economy. People can observe and experience the state of the economy in their every day life (Haller & Norpoth, 1997). Individuals may pay greater attention to economic news only during times of economic slowdowns (Wu, Stevenson, Chen, & Guner, 2002). Moreover, economic news covers a broad range of topics. Thus, it is hard to define the boundaries of economic news. These make the study of the connection between economic news and public opinion complex and complicated.

This study focuses on the relationships among the news coverage of the economy as embodied in the economic section of Business Week magazine, arguably the most widely read source of global business news in the United States, the CCI, and the real state of the economy. On the one hand, this study examines if the CCI reflects the tone of Business Week’s economic section. In other words, does economic reporting of Business Week impact the CCI? If so, does the tone of economic reporting of Business Week impact the CCI more than the real state of the economy does? On the other hand, this study also examines the effects of the CCI on both the tone of Business Week and the real state of the economy.
CHAPTER 2

LITERATURE REVIEW AND THEORETICAL FRAMEWORK

This chapter examines the role of the Index of Consumer Confidence (CCI) in the business sector and introduces the study’s theoretical framework, agenda setting. Previous studies that have explored the relationship between economic news and consumer sentiment are also reviewed. The last part of the chapter outlines the study’s research questions.

Business Cycles and Consumer Sentiment

The term “business cycle” or “economic cycle” has been used to describe the “ups and downs of business” since the end of the seventeenth century. Fluctuations in business cycles are often portrayed in four phases: “An upturn ends at an upper turning point, followed by a downturn, which leads to a lower turning point. Then the upturn starts again” (Oppenlander, 1997a). This general movement is consisting of periods of economic expansion and periods of economic decline or contraction. Figure 1 describes this phenomenon (QuickMBA, 2008).

Business cycles are represented by a series of economic variables or indicators such as consumer prices, industrial output, employment, consumer spending and level of investment (Long & Plosser, 1983; Oppenlander, 1997a). The “expansion” refers to the time frame where economic activity, measured by economic indicators such as output, employment, income and sales, is increasing. During the “recession” period, economic activity is in decline, usually signified by reductions in output, employment, income and sales (ECRI, 2007).

Aside from describing current economic conditions and serving as tools to analyze the potentials for economic growth, business cycle indicators can also serve as business
forecasting devices. Both consumers and those who engage in business always have opinions or sentiments about the market (Oppenlander, 1997b). The business climate and the consumers’ sentiment are clear reflections of these business cycles (Strigel, 1981). If sentiment regarding the business is more favorable than the real business situation would suggest, a cyclical upswing is forecasted; if sentiment is worse than the real business situation, a downturn is predicted (Figure 2). The business cycle indicator which expresses this sentiment the best is considered the leading and the most useful indicator.

Figure 1. The phases of the business or economic cycle (QuickMBA, 2008)
Agenda-setting Theory and Consumer Sentiment

The CCI is an indicator of the public’s opinion of the U.S. economy often made accessible to the public through the mass media. According to the agenda-setting theory, the media have the power to tell the public what to think about, which represents a kind of first-level effect. But the influence of the media on public opinion goes beyond that. The media not only tell the public what to think about; media also tell people how to think about an issue, and what to think, which is often referred to the second-level agenda-setting effect (McCombs & Shaw, 1993).

Agenda-setting

Mass communication scholars have used agenda-setting theory as a core conceptual framework for understanding media effects for more than 30 years (Kiousis, 2005). Since...
McCombs and Shaw published their seminal article in 1972, more than 350 articles about agenda-setting have been published until 1996 (Dearing & Rogers, 1996). Initially, agenda-setting primarily studied how the mass media, policy makers and the public interacted and influenced each other to transfer the salience of “objects” in the news media to the public (Kiousis & McCombs, 2004). In their first study about agenda-setting and political news in 1972, McCombs and Shaw submitted that what most people know comes to them “second-” or “third-” hand from the media or other people. They hypothesized a positive relationship between the mass media agenda and audience agenda, and concluded that the mass media not only transmit issues to the public, but also tell them how important those issues are by the intensity of reports and the position of issues in the media agenda (McCombs & Shaw, 1972). The second phase of McCombs and Shaw’s work was published in 1977 in which they not only replicated their original findings, but also investigated the contingent conditions that enhance or limit agenda-setting (McCombs & Shaw, 1993).

**Second-level Agenda-setting and Consumer Sentiment**

Recently, agenda-setting research has been expanded to an examination of second-level effects. Rather than focusing on the topics the news media cover, second-level agenda-setting investigates how the media cover those topics and the impact of that coverage on issue salience (Kiousis, 2005; Kiousis & McCombs, 2004). In contrast to objects (i.e., issues, political candidates, etc.), second-level agenda-setting shifts its attention to “perspectives or frames that journalists and the public employ to think about each object” (Ghanem, 1997). These perspectives can direct people’s attention to or away from attributes of objects. The selection of objects for attention and the selection of frames for thinking about these objects both demonstrate
the powers of agenda-setting. Journalists’ judgments of an item’s newsworthiness can make them frame issues in a broad range of ways (McCombs & Shaw, 1993).

Second-level agenda-setting offers new challenges and opportunities for mass communication researchers because it implies a deeper and more thorough processing of media content (Wanta, Golan & Lee, 2004).

Since the CCI is considered to be a principal indicator of how people feel about the U.S. economy, the study of the relationships between economic reporting by mass media and the CCI can be examined through the second-level agenda-setting theory. The monthly reports of the CCI include how people evaluate business conditions and employment conditions, their plans to buy automobiles, houses, and their plans of vacation. Thus, it is appropriate to use the CCI to present an audience agenda which is about how people feel about the U.S. economy.

Studies about Agenda Setting and Consumer Sentiment

Some previous studies have investigated the complex relationships among news coverage of the economy, the real state of the economy, and the public’s perception of the economy (consumer sentiment). Only a few of them have found that the media have powerful effects on the public’s opinion of the economy. These studies mainly suggest that consumers learn about the economy primarily from media’s interpretation of it (Boef & Kellstedt, 2004). Alsem, Brakeman, Hoogduin and Kuper (2004), who studied the Dutch newspapers’ reporting on the economy, found that public sentiments could be magnified by the “spin” that the media give to their stories. The spin results from the competition to write memorable stories. Consequently, it can be surmised that consumer sentiment can be affected not only by economic fundamentals, but also by the way these fundamentals are reported in
the media. When conducting content analysis of economic news coverage on the front pages of the *New York Times* from 1981 to 1992, Goidel & Langley (1995) used a measure of a news story’s tone (positive or negative), the same month’s measurement of public opinion and the same month’s indicators of the real state of economy, and then concluded that news coverage of the economy—particularly negative coverage—does have a significant influence on public opinion even after controlling for the effects of real-world economic indictors.

There is more empirical evidence that suggests, however, that news coverage only has a limited effect on the public’s perception of the economy. Some researchers submit that people’s perception of the economy is greatly shaped by what they personally observe and experience in their everyday lives (Linden, 1982). Behr and Iyengar (1985), who have examined the interrelationship among real-world cues, television news coverage and public concern for the issues of inflation, energy, and unemployment, have found that overall news coverage was not influenced by fluctuations in public concern. Rather, media coverage was more likely led by actual events. Haller and Norpoth (1997) have asserted that news actually plays only a small role in providing people with economic information. Close to half of Haller and Norpoth’s respondents reported not getting any economic news at all. More importantly, news exposure was found to be not particularly helpful in significantly improving people’s ability to evaluate economic situations. Rather, they found that the indicators of real economic condition such as inflation and unemployment contributed more to the public opinion of the economy.

In another agenda-setting study designed to determine the relationship between economic media coverage and public opinion, Stevenson, Gonzenbach and David (1994) identified cyclical effects between media coverage of the economy and people’s perception of
the economy. Controlling for real-world economic indicators, they found that public opinion at first strongly influenced corresponding media coverage. However, the media then reacted to public opinion and were actually found to exert influence on public opinion only at a later date.

Some previous studies explored media effect of public opinion during some specific time periods and found that news coverage does impact public opinion, but this only happens during recession or times of economic slowdown. For example, Doms and Morin (2004) suggest that consumers receive signals about the economy through the tone and volume of economic reporting. Unfortunately, what consumers watch or read may not be consistent with actual economic events, especially during the early 1990s. As a consequence, consumers update their expectations about the economy much more frequently during periods of high news coverage than during periods of low news coverage. High news coverage of the economy is often experienced during and immediately after recessions.

Using advanced vector auto-regression analysis and controlling for leading economic indicators, Blood & Phillips (1995) found that only news articles containing recession headlines influenced consumer attitudes.

Wu, Stevenson, Chen and Guner (2002) also examined newspaper stories about economic recessions between 1987 and 1996 and found that media coverage could be a good predictor of the public’s assessment of the economy during downturn periods even after the state of the economy was controlled for. They suggested that individuals pay greater attention to economic news during times of economic slowdowns.

Hester and Gibson (2003) studied the specific influence of the tone of media coverage on general public perception of current and future economic performance from a second-level agenda-setting perspective and through time series analysis. They found that news
coverage framed the economy more in negative terms. They also found no evidence to support the hypothesis that negatively framed news stories about the economy would be a more significant predictor of attitudes toward current economic conditions than positively framed news coverage. However, their results strongly supported the hypothesis that negatively framed news coverage of the economy is a better predictor of corresponding attitudes toward future economic conditions than positively framed news coverage. Their assumption is that people use personal experiences to make judgments whenever possible, but rely more on the media for issues out of their reach (Hester & Gibson, 2003).

**Obstacles to Agenda-setting**

Previous studies also suggest that agenda-setting may not occur all the time. In other words, there are situations in which the media agenda may not influence the audience agenda, which suggests that this study may find out that economic reporting may have no effect on the CCI.

There are numerous potential reasons for these limited agenda-setting effects on the public. Eight of these reasons have been suggested: 1. The issues the public is interested in change over time; 2. Historical events, which draw the public attention, interfere with the agenda-setting process; 3. Certain issues may receive inconsistent coverage in the press; 4. Public officials may intervene to focus or detract the public’s attention on some important issues; 5. Some issues are considered as “pet” issues which the public may consider to be the nation’s most important problems; 6. Under some conditions, the audience agenda may influence the media agenda; 7. Different media content may affect each other; and 8. Media coverage is influenced by episodic cycles of issue reporting (Wanta & Mahmoud, 1990).
Research Questions and Theoretical Models

Based on the foregoing literature review, this study asks:

RQ1: Does the tone (positive, negative or neutral) of the U.S. economy section of Business Week have a significant corresponding impact on the CCI significantly?

RQ2: Does the CCI have a significant corresponding impact on the tone (positive, negative or neutral) of the U.S. economy section of Business Week?

RQ3: Does the real state of the economy predict the CCI significantly?

RQ4: In general, is the tone (positive, negative or neutral) of the U.S. economy section of Business Week a better predictor of the CCI than the real state of the economy is?

RQ5: During recession or time of economic slowdowns, do the results of any of the questions above change?

Based on the research questions shown above, the possible relationships among the business cycles, media and consumer sentiment can be explained by the models shown below. The first model in Figure 3 suggests that business cycles have much more powerful corresponding influence on the CCI than media do, which reflect business cycles and in the meanwhile have some limited impact on the CCI. The second model in Figure 4 provides alternative suggestion that media have a more powerful corresponding impact on the CCI than business cycles do. The third model 3 shown in Figure 5 proposes that media, rather than being a predictor of the CCI, are in fact influenced by the CCI significantly.
Figure 3. The relationship among business cycles, consumer sentiment and media

Figure 4. The relationship among business cycles, consumer sentiment and media

Figure 5. The relationship between consumer sentiment and media
CHAPTER 3

METHODOLOGY

This study focuses on the relationships among the news coverage of the economy as embodied in the economic section of *Business Week* magazine, the Index of Consumer Confidence and the real state of the economy. Data for this study were gathered using content analysis, plus the use of real economic data and CCI data.

**Operationalization of Variables**

A table of independent variables and dependent variables for each research question is shown below (Table 1).

<table>
<thead>
<tr>
<th>Research question</th>
<th>Independent variables</th>
<th>Dependent variables</th>
</tr>
</thead>
<tbody>
<tr>
<td>Q1</td>
<td>Tone of <em>Business Week</em></td>
<td>CCI</td>
</tr>
<tr>
<td>Q2</td>
<td>CCI</td>
<td>Tone of <em>Business Week</em></td>
</tr>
<tr>
<td>Q3</td>
<td>The real state of the economy</td>
<td>CCI</td>
</tr>
<tr>
<td>Q4</td>
<td>CCI</td>
<td>The real state of the economy</td>
</tr>
</tbody>
</table>

Considering the research questions, the following variables need to be operationalized:

1). *Tone of Business Week*.
2). *CCI*;
3). *The real state of the economy*. 
1). *Tone of Business Week.*

Content Analysis

Because this study uses agenda-setting as the theoretical framework, it is appropriate to use content analysis to determine the economic agenda of the magazine *Business Week*, a leading publication that deals with business and economic issues in the nation.

Content analysis is a method of media research that focuses on the symbols and messages contained in the mass media. There are many definitions of content analysis. Kerlinger (2000) offers a fairly typical one: Content analysis is a method of studying and analyzing communication in a systematic, objective, and quantitative manner for the purpose of measuring variables. This definition involves three characteristics of content analysis. First, the sample selection and the evaluation processes must be systematic, and the coding and analysis procedures must be uniform. Second, the findings must minimize researcher bias. Third, content analysis is primarily a quantitative research method (Wimmer & Dominick, 2002).

Many content analysis studies compare media content to “real world” indicators. In these studies, researchers match the portrayal of a certain group, phenomenon or event in the media against some predetermined measurements usually from government, private industry or other official sources. Using this technique, Davis (1951) found no relationship between the crime coverage of Colorado newspapers and the state’s actual crime rate. Gerbner (1969) compared the incidence and intensity of televised violent content with real life social indicators of violence. Taylor and Bang (1997) compared the extent to which African-Americans and Latinos are portrayed as lawbreakers in television shows with the actual crime records of these groups. In a similar vein, this study examines whether economic
reporting on *Business Week* is somehow associated with the actual state of the economy data as well as the Index of Consumer Confidence.

This study focuses on the headlines of the U.S. economy section of *Business Week*. Compared to lead paragraphs and the full text, headlines can be used to roughly estimate the broad contours of news coverage and usually adequately represent original content when researchers are working at a high level of aggregation (Althaus, Edy, Phalen, 2001).

Moreover, it is more difficult to achieve reliability with whole text than with headlines when coding (Weber, 1990). In the whole text of the U.S. economy section in *Business Week*, authors usually shift tones several times, but the tone of headlines is clearer, which may help to achieve acceptable reliability. Therefore, this study uses headlines’ monthly averages as units of analysis.

**Coding Rules**

The *tone of Business Week* refers to the general orientation of the headlines with respect to some economic topic or issue or with reference to the condition of the economy in general. Because the “economy” is an abstract term, in the absence of this word, concrete economic indicators mentioned within the headline were used to find “signals.” These indicators include those that have something to do with unemployment or employment, consumer prices, industrial output, gross domestic product (GDP), the stock market, housing, consumer spending, investment, and so on. In addition, coders were asked to examine the headlines for the presence of phrases and terms that may also serve as “signals.” Because readers may find economic data or indicators difficult to understand, these signals helped set up the tone of an article for them.

In this study, there are three potential tones each headline might exhibit:
1. **Positive** (coded 1) means that the headline sees the economy as growing, and generally portrays optimism about the economic potential. These headlines contain positive phrases, adjectives or adverbs such as “a strong job market,” “strongest gain,” “strong sales,” “strong domestic spending,” “further acceleration,” “good profit,” “good mood,” “the largest advance,” “solid support” and “stood far above.” Terms such as “low unemployment,” “high consumer spending,” and “high industrial output” will also be considered as positive signals. Economic growth can be described in very strong terms (i.e., “overheating,” “boiling,” “aflame,” and “on fire”). These terms also indicate that the story displays a positive spin on the economy (Moffatt, 2007).

2. **Neutral** (coded 0), means that the headline evaluates the current state of the economy as maintaining its previous position. Headlines that demonstrate the absence of positive or negative comments about the economy (or some aspect of it) also fell under this category. If positive and negative were mixed together in an headline without a clear interpretation of whether the economy was in good or bad shape, the headline was coded as neutral.

3. **Negative** (coded -1) means that the headline sees the economy as slowing down or declining. Reports that deal with setbacks and other conditions that may dampen economic activity also received this code. Negative phrases or terms such as “unemployment is getting worse,” “highest jobless rate,” and “dismal start” fell under the negative category.

Since the economy itself contains so many indicators, some additional rules of coding were provided to help coders to determine the tone of headlines more appropriately (Table 2).
Table 2. Rules of coding

<table>
<thead>
<tr>
<th>Priority of Indicators</th>
<th>Positive</th>
<th>Negative</th>
<th>Neutral</th>
</tr>
</thead>
<tbody>
<tr>
<td>1 Economy, Demand, GDP, growth, etc.:</td>
<td>robust, hot, get momentum, strong, surging, recovery</td>
<td>weak, soft, recession</td>
<td>not bad, not weak</td>
</tr>
<tr>
<td>2 joblessness, job, unemployment, labor market</td>
<td>tight, strong, firm</td>
<td>weak, soft</td>
<td>not bad, not weak</td>
</tr>
<tr>
<td>3 Inflation, interest rate, price</td>
<td>pressure, hike, increase</td>
<td>no inflation, no worry</td>
<td></td>
</tr>
<tr>
<td>4 consumer spending, business investment or spending, manufactory output</td>
<td>strong</td>
<td>weak</td>
<td>not bad, not weak</td>
</tr>
<tr>
<td>5 housing, bond market</td>
<td>strong</td>
<td>weak</td>
<td>not bad, not weak</td>
</tr>
<tr>
<td>6 Trade(import, export) gap</td>
<td>shrinking</td>
<td>deficit</td>
<td></td>
</tr>
</tbody>
</table>

As Table 2 shows, there are priorities of the six rows: 1>2>3> (4, 5 and 6).

When the economy was strong, then no matter whether the job market and inflation or other indicators were positive or negative, coders coded it as positive. If economy was weak, coders coded it as negative and ignored other indicators.

In addition, the weight of the job market was greater than inflation pressure. The weight of inflation pressure was greater than other indicators such as housing, bond, trade and manufactory output.

Indicators in rows 4, 5 and 6 are at the same level. In this case, when indicators in these categories move in different directions, coders compared the numbers of positive and negative indicators, and determined the tone. For example, housing was weak but the bond
market was strong and output was increasing. Coders coded this example as positive according to one negative indicator and two positive indicators.

For any indicator for which there was no strong valence, coders coded it as neutral.

Since the CCI is issued monthly, the coded headlines of articles in Business Week were grouped on a monthly basis. To do this, coders coded each headline, and the monthly total scores were averaged.

**Sample Selection**

To ensure that the headlines that would be examined discuss the U.S. economy over time in a uniform way, a special Economy Section of Business Week was selected. A census of each week’s Economy Section headlines published from January 1997 to December 2006 was analyzed.

A 10 year time frame was selected for two reasons. First, a 10 year period was needed in order to include a complete business cycle. From 1997 to 2006, the U.S. economy experienced good years during 1997 to 1999, a recession period around 2001, and a recovery process after 2002.

Second, this study used multivariate analysis, which requires larger samples than do univariate studies. In this case, a sample size of 500 is “very good” (Comrey and Lee, 1992). A preliminary search for the target articles from 1997 to 2006 using the search engine Business Source Elite produced a total of 500 headlines from 120 months, which is a good sample size for this study.

In order to test whether media have more influence during times of recessions, headlines of articles in the U.S. economy section around the recent recession and the following recovery period were also examined. According to the National Bureau of
Economic Research (NBER), the recent recession began in March 2001 and ended in November 2001. Moreover, real personal income fell in early 2001. It reached its low point in October 2001 and then generally rose throughout 2003, reaching its highest level in July 2003. Employment reached a peak in February 2001 and declined through July 2002. It rose slightly through November 2002, but with the exception of January 2003, declined throughout 2003 until it rose in September 2003. GDP reached a peak in the fourth quarter of 2000. This was followed by contraction during the first three quarters of 2001 and growth since then (NBER, 2008). Based on these data, this study chose the period from January 2001 to December 2003 (36 months) to explore if media has greater impact on public opinion during a recession or time of economic slowdown. A total of 150 headlines were included in this period.

**Intercoder Reliability**

According to Wimmer and Doninick (2002), “A study is reliable when repeated measurements of the same material result in similar decisions or conclusions.” Using the same instruments, independent coders code the same material, and then measure agreement levels, called intercoder reliability.

To enhance intercoder reliability, category boundaries must be clearly defined. Coders need to be trained carefully. To do this, coders will receive a copy of the codebook containing the category definitions, coding guides and examples, which the researcher will discuss with them. The coding scheme will then be pilot-tested so that poorly defined categories can be detected, and chronically dissenting coders can be identified. After the training and the pilot study, coders will receive a revised version of the codebook, and the formal intercoder reliability test will be conducted.
To ascertain intercoder reliability, this study used Holsti’s (1969) formula,
\[
\text{Reliability} = \frac{2M}{N_1 + N_2},
\]
where \(M\) is the total number of the headlines two coders coded in common, and \((N_1 + N_2)\) is the total number of coding decisions made by the two coders. In this study, a result greater than 75% is desired (Wimmer & Dominick, 2002).

Two coders conducted the intercoder reliability test to code 50 headlines of *Business Week* and obtained 84% reliability, which was judged to be acceptable. The plot of monthly data of the tone of *Business Week* from 1997 to 2006 is shown in Figure 6.

![Figure 6. The tone of Business Week from 1997 to 2006](image)

2) *CCI*

Data about the Index of Consumer Confidence (CCI) from January 1997 to December 2006 were obtained from the website of PollingReport.com, an independent, nonpartisan resource on trends of American public opinion. Figure 7 shows the time series plot of the CCI.
3). The real state of the economy.

The real state of the economy, depicted in business cycles, is depicted by a broad range of economic indicators such as employment, industrial output, gross domestic product (GDP) and consumption. This study uses the Standard & Poor’s 500 (S&P 500) to represent the real state of the economy. Standard & Poor’s U.S. indices are designed to reflect the U.S. equity markets and, through the markets, the U.S. economy. The S&P 500 focuses on the large-cap sector of the market; however, since it includes a significant portion of the total value of the market, it also represents the market. Widely regarded as the best single gauge of the U.S. equities market, this world-renowned index includes a representative sample of 500 leading companies in leading industries of the U.S. economy. Although the S&P 500 focuses on the large-cap segment of the market, with about 75% coverage of U.S. equities, it is also an ideal proxy for the total market. The index is the most notable of the many indices owned and maintained by Standard & Poor's, a division of McGraw-Hill. All of the stocks in the index are those of large publicly held companies and trade on the two largest U.S. stock markets,
the New York Stock Exchange and Nasdaq. After the Dow Jones Industrial Average, the S&P 500 is the most widely watched index of large-cap US stocks. It is considered to be a bellwether for the U.S. economy (Standard & Poor’s, 2007).

The data of the S&P 500 from January 1997 to December 2006 were obtained from the website of the Standard & Poor’s (2008). Figure 8 shows the time series plot of S&P 500. Figure 9 shows the plots of the three time series together.

![Figure 8. The S&P 500 from 1997 to 2006](image)

![Figure 9. The standardized data plots of the tone of Business Week, the CCI and the S&P 500 from 1997 to 2006](image)
Data Analysis

This study conducted time series multivariate tests to examine possible interrelationships among variables. The data were analyzed using the programs R 2.6.1, S-PLUS 6.2 and the Statistical Package for Social Sciences v. 15.

Cross-lagged Studies

Cross-lagged correlation studies used to be an important method to test the agenda-setting relationship over time. The logic behind cross-lagged correlation analysis is that if one variable is a possible cause of another, then the correlation between X (the cause) at Time 1 and Y (the effect) at Time 2 should be greater than the correlation between X at Time 2 and Y at Time 1 (McCombs, 1977). Recently, for agenda setting over time, researchers concluded that simple cross-lagged analysis is seriously flawed since it only measures the relationship of media agenda and public agenda at two time periods. In other words, when historical effects are presumed, the cross-lagged relationship of media agenda and public agenda should be measured at more than two time periods (Gonzenbach, 1996).

Granger Causal Analysis

Smith (1987) studied news coverage and public concern about community issues using a time series analysis of the data from 1974 to 1981. In Smith’s study, the cross-correlation function between newspaper coverage and public concern for each issue over time was identified and a Granger causal analysis was conducted. The analysis of cross-lagged studies has interpreted the correlations among time series but has not adequately indicated the causal relationships among those variables. The over time causality in longitudinal data can be determined by the Granger causal analysis (Freeman, 1983). A variable X is a “Granger cause”
of a variable Y if Y is better predicted by the past histories of both X and Y rather than by the past histories of Y alone (Freeman, 1983; Smith 1987; Rogers, Dearing & Chang, 1991).

Below are causal relationships that are examined through the Granger causal analysis.

1. An instantaneous causal link occurs when the present and the past history of one time series increase the other’s total variance explained.

2. A one-way causal relationship occurs if one time series explains the other, but the latter one does not explain the former one when both the two time series are included in regression equations in which each is dependent.

3. A feedback or reciprocal causal relationship occurs when two time series contribute equally to explain each other’s variance.

4. Finally, the absence of Granger causality is determined when neither of two series contributes to increase the other’s variance explained by including their past histories for the other. (Rogers, Dearing and Chang, 1991)

As was discussed above, Granger causal analysis is an appropriate method to analyze agenda setting effects overtime in this study. Before testing Granger causality between any two time series, the contribution of each time series’ past histories upon itself must be determined. Thus, the univariate analysis of each time series is the first step of Granger causal analysis.

This study applied ARIMA analysis to model each time series. Box and Jenkins (1976) developed an identification-estimation-diagnosis procedure to determine the patterns of past histories of a given time series, and therefore to sort out the stochastic component (“white noise” or “random disturbance”) of the time series. The identification procedure is to determine whether a given time series has an autoregressive component (AR), or a moving
average component (MA), or a trend component (I), the three components with which together constitute an ARIMA model. It is very important that the three parameters, autoregressive parameter \( p \), moving average parameter \( q \) and trend \( d \), must be modeled before Granger causality is examined since the findings of the relationships between any two time series will be inaccurate if these parameters are not adequately modeled. The diagnosis procedure provides evaluations to examine whether the ARIMA model established is the best fit for a given time series (Box and Jenkins, 1976; Rogers, Dearing & Chang, 1991; Gonzenbach, 1996). Akaike information criterion (AIC), one of model selection criteria based on residuals, is used with other diagnostics of residuals, to check whether the ARIMA term in a given time series is a best model, which removes the systematic or the deterministic component of the series, leaving behind only the stochastic component (Wei, 1990).

The second step of Granger causal analysis is to conduct bivariate analysis of the relationships between each of the time series pair based on the determined ARIMA components of each time series.
CHAPTER 4

RESULTS AND DISCUSSION

Results

ARIMA model analysis

The first parameter to a model is trend $d$, which is the motion or trend of a specific direction within a series – upward or downward – or any systematic change in the level of a time series (McCleary & Hay, 1980). In the identification stage, according to the plots of the three time series, this study found that all three time series showed a secular trend or cyclicality, or nonstationarity, which means that a systematic increase or decrease in a series distribution over time occurs, or $d=1$. Therefore, the three time series (tone of *Business Week*, the CCI, and the S&P 500) were first-order differenced to remove the linear trend from each one in order to apply the Box and Jenkins procedure which requires that all time series be stationary (Rogers, Dearing & Chang, 1991) (Figure 10, Figure 11, Figure 12).

![Figure 10. The first-order difference of the tone of *Business Week* from 1997 to 2006]
Figure 11. The time series plot of the first-order difference of the CCI from 1997 to 2006

Figure 12. The time series plot of the first-order difference of the S&P 500 from 1997 to 2006

Through the Box and Jenkins procedure, the ARIMA components of each time series were determined. Table 3 shows the ARIMA terms for each time series and the total amount of variance explained by the ARIMA model of itself ($R^2$).
After taking the first order difference of the time series CCI and the S&P 500, this study selected trivial models or white noise as the models of the two time series. The AR(3) model was selected for the first-order differenced time series of the tone of *Business Week.*

### Table 3. Univariate ARIMA coefficients and variance explained for each time series (1997 – 2006)

<table>
<thead>
<tr>
<th>Time series</th>
<th>ARIMA term</th>
<th>Coefficients**</th>
<th>R²</th>
</tr>
</thead>
<tbody>
<tr>
<td>Tone of Business Week***</td>
<td>(3,1,0)</td>
<td>AR(3)=-.4914 * (0.0897); -.2482* (0.0975); -.2008* (0.0891)</td>
<td>0.215*</td>
</tr>
<tr>
<td>CCI***</td>
<td>(0,1,0)</td>
<td>0</td>
<td></td>
</tr>
<tr>
<td>S&amp;P 500***</td>
<td>(0,1,0)</td>
<td>0</td>
<td></td>
</tr>
</tbody>
</table>

* Indicates the coefficient is significant at p<.001.
**AR is autoregressive; MA is a moving average. The number in the parentheses following each AR or MA is the time lag in months. The number following each AR or MA term is the standard error of each coefficient of the ARIMA term.
*** These series are first order differenced.

### Granger causal analysis

In order to do bivariate analysis, transfer function models were constructed by adding the past histories of the independent series to the dependent series. Before constructing the transfer function models, a decision must be made about which lagged coefficients of the independent time series come to be included into the regression equations to explain the dependent series. This decision can be made based on the cross-lagged correlations between each two time series. A Pearson correlation test was conducted to calculate the cross-lagged correlations between the two time series of the tone of *Business Week* and the CCI at the T-0 point, the positive lags (i.e. with *Business Week* leading the CCI by 1, 2, 3, 4 and 5 months) and the negative lags (i.e. with the CCI leading *Business Week* by 1, 2, 3, 4 and 5 months). The cross-lagged correlations at the positive lags and those at the negative lags do not necessarily equal to each other (Smith, 1987). The same procedure of the Pearson correlation test and analysis were conducted between the time series of the S&P 500 and the CCI and
between the time series of the S&P 500 and tone of *Business Week*. Table 4 shows the results of the analysis.

**Table 4. Cross-lagged correlations among the CCI, the S&P 500 and the tone of *Business Week* from Time t-5 to Time t+5 (1997 – 2006)**

<table>
<thead>
<tr>
<th>Variable at time 0</th>
<th>S&amp;P500***</th>
<th>CCI***</th>
<th>Business Week***</th>
</tr>
</thead>
<tbody>
<tr>
<td>Lagged Variable</td>
<td>-5</td>
<td>-4</td>
<td>-3</td>
</tr>
<tr>
<td>CCI***</td>
<td>0.146</td>
<td>0.044</td>
<td>-0.062</td>
</tr>
<tr>
<td></td>
<td>-4</td>
<td>-0.090</td>
<td>0.024</td>
</tr>
<tr>
<td></td>
<td>-3</td>
<td>-0.034</td>
<td>-0.004</td>
</tr>
<tr>
<td></td>
<td>-2</td>
<td>0.179**</td>
<td>0.074</td>
</tr>
<tr>
<td></td>
<td>-1</td>
<td>0.324*</td>
<td>-0.004</td>
</tr>
<tr>
<td></td>
<td>0</td>
<td>0.168*</td>
<td>-0.045</td>
</tr>
<tr>
<td></td>
<td>1</td>
<td>0.028</td>
<td>0.007</td>
</tr>
<tr>
<td></td>
<td>2</td>
<td>-0.017</td>
<td>0.011</td>
</tr>
<tr>
<td></td>
<td>3</td>
<td>-0.139</td>
<td>0.011</td>
</tr>
<tr>
<td></td>
<td>4</td>
<td>-0.034</td>
<td>0.023*</td>
</tr>
<tr>
<td></td>
<td>5</td>
<td>0.021</td>
<td>0.011</td>
</tr>
</tbody>
</table>

*Significant at p<.05.
**Significant at p<.01.
*** These series are first order differenced.

---

**Table 5. Transfer function coefficients, total variance (R^2) explained, and incremental variance due to the predictors of the independent series (1997 - 2006)**

<table>
<thead>
<tr>
<th>Dependent series (Y)</th>
<th>Independent series (X)</th>
<th>Transfer function coefficient</th>
<th>Standard error of coefficient</th>
<th>Total R^2</th>
<th>Incremental R^2</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>CCI***</td>
<td><em>Business Week</em>**</td>
<td>2.417_t-1*</td>
<td>1.14</td>
<td>0.037</td>
</tr>
<tr>
<td></td>
<td><em>Business Week</em>**</td>
<td>CCI***</td>
<td>-.018_t-4**</td>
<td>0.007</td>
<td>0.264</td>
</tr>
<tr>
<td>2</td>
<td>CCI***</td>
<td>S&amp;P 500***</td>
<td>0.025_t*</td>
<td>0.011</td>
<td>0.181</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>0.045_t-1**</td>
<td>0.011</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>0.023_t-2*</td>
<td>0.011</td>
<td></td>
</tr>
<tr>
<td></td>
<td>S&amp;P 500***</td>
<td>CCI***</td>
<td>1.36_t</td>
<td>0.715</td>
<td>0.3</td>
</tr>
<tr>
<td>3</td>
<td><em>Business Week</em>**</td>
<td>S&amp;P500***</td>
<td>0.001_t</td>
<td>0.001</td>
<td>0.232</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>15.173_t</td>
<td>8.981</td>
<td>0.024</td>
</tr>
</tbody>
</table>

*Significant at p<.05.
**Significant at p<.01.
*** These series are first order differenced.
The lagged coefficients with statistically significant correlations in the correlogram were used to test the prediction series’ contribution to explaining the dependent series over time (Rogers, Dearing & Chang, 1991). The selected lagged coefficients in each time series are shown in the Table 5.

Based on the analysis above, transfer function models of the dependent series were constructed. Transfer function analyses produce transfer function coefficients, which indicate the dynamic, cyclical relationships between each of the time series pairs and reveal the statistical significance of each predictor’s contribution and its direction in affecting the dependent series. Take the transfer function analysis of the CCI and the tone of Business Week for example. The transfer function equations regarding the two variables are shown below (R-1 & R-2).

\[ C = 2.417B_{t-1} + a_t \]  \hspace{1cm} (R-1)

Where C is the CCI*** and B is the tone of Business Week***, \( a_t \) is an error, \( a_t \sim \text{nid}(0, 38.695) \).

\[ B = -.018C_{t-4} - .489B_{t-1} - .224B_{t-2} - .193B_{t-3} + a_t \]  \hspace{1cm} (R-2)

Where \( a_t \) is an error, \( a_t \sim \text{nid}(0, 1.643) \).

The reason for one coefficient is much less than the other one (i.e. 2.417 vs. -0.018) is that after taking the first order difference, the CCI and the tone of Business Week still have different ranges of variance (CCI: [-18.0, 19.6]; Business Week: [-1.27, 1.10]).

Transfer function analyses also provide \( R^2 \), which is the proportion of the total variance of the dependent series explained by its past histories, the ARIMA component, plus the independent series Estimates of the incremental variance solely explained by the prediction series over and above the dependent series itself can be made through subtracting the \( R^2 \) of
the univariate ARIMA models from the $R^2$ of the transfer function models. The statistical significance of the incremental variance is determined by the F-test. The F-test for the incremental variance jointly tests the statistical significance of all the included predictors of the independent series in the transfer function analyses. For example, R-3 shows the reduced model of the dependent variable $Y$, and R-4 shows the complete model of $Y$.

\[
Y = Y_1 \quad \text{(R-3)} \\
Y = Y_1 + X_1 \quad \text{(R-4)}
\]

Where $Y_1$ is the past history of $Y$ which can predict $Y$, $X_1$ is all the included predictors of the independent variable $X$ which can predict $Y$. The incremental variance is the difference between the variance of $Y$ explained by the complete model and that explained by the reduced model. Table 5 shows the results of four transfer function analyses for each of the time series pair.

**Mutivariate analysis**

The bivariate analysis discussed above has shown that the impact of tone of *Business Week* on the CCI is less than the impact of the S&P 500 on the CCI. The proposed model 1 shown in the Figure 3 may explain the result, which indicates that media agenda is just an intervening variable. The multivariate analysis was conducted to verify the relationships among the three variables.

The S&P 500 at time 0, time -1 and time -2, and the tone of *Business Week* at time -1 were chosen as predictors since they have significant correlations with the CCI at time 0. The reduced model predicting the CCI over time is shown below (R-5).

\[
C_t = 0.027S_t + 0.042S_{t-1} + 0.024S_{t-2} + 2,153B_{t-1} + a_t \quad \text{(R-5)}
\]
Where C is the CCI***, S is the S&P 500***, and B is the tone of Business Week***, \( a_t \) is an error, \( a_t \sim \text{nid}(0, 31.391) \).

Table 6. Transfer function coefficients and incremental variance due to the predictors of the independent series in the multivariate analysis (1997 – 2006)

<table>
<thead>
<tr>
<th>Independent series</th>
<th>Transfer function coefficient</th>
<th>Standard error of coefficient</th>
<th>Total R(^2)</th>
<th>Incremental R(^2)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1 S&amp;P 500***</td>
<td>0.027*</td>
<td>0.011</td>
<td>0.209*</td>
<td>0.172**</td>
</tr>
<tr>
<td></td>
<td>0.042(_t)*</td>
<td>0.011</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>0.024(_t)(_t)*</td>
<td>0.011</td>
<td></td>
<td></td>
</tr>
<tr>
<td>2 Business Week***</td>
<td>2.153(_t)*</td>
<td>1.074</td>
<td>0.209*</td>
<td>0.028*</td>
</tr>
</tbody>
</table>

*Significant at p<.05.
**Significant at p<.01.
*** These series are first order differenced.

Table 6 shows the results of the analysis based on the reduced model (R-1), which indicates that the tone of Business Week explains only 2.8% of variance of the CCI, and the percentage of the variance of the CCI significantly explained by the S&P 500 (17.2%) is much greater than that explained by the tone of Business Week. These results are very close to the results of the bivariate analysis shown above.

**Time Series Analysis of Times of Economy Slowdowns**

The same ARIMA model analysis, Granger causal analysis and multivariate analysis were used to examine whether or not effects during the 2001 to 2003 recession would be stronger than overall effects over time. The results are shown in Table 7, Table 8 and Table 9.

Table 7 indicates that after taking the first order difference, the time series of the CCI and the S&P 500 became white noise, and the time series of the tone of Business Week became an AR (1,) model.
Table 7. Univariate ARIMA coefficients and variance explained for each time series (2001 – 2003)

<table>
<thead>
<tr>
<th>Time series</th>
<th>ARIMA term</th>
<th>Coefficients**</th>
<th>R²</th>
</tr>
</thead>
<tbody>
<tr>
<td>Tone of Business Week***</td>
<td>(1,1,0)</td>
<td>AR(1)=0.4369*</td>
<td>0.177*</td>
</tr>
<tr>
<td>CCI***</td>
<td>(0,1,0)</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>S&amp;P 500***</td>
<td>(0,1,0)</td>
<td>0</td>
<td>0</td>
</tr>
</tbody>
</table>

* Indicates the coefficient is significant at p<.001.
**AR is autoregressive; MA is a moving average. The number in the parentheses following each AR or MA is the time lag in months. The number in the below each AR or MA term is the standard error of each coefficient of the ARIMA term.
*** These series are first order differenced.


<table>
<thead>
<tr>
<th>Variable at Time 0</th>
<th>Lagged Variable</th>
<th>-5</th>
<th>-4</th>
<th>-3</th>
<th>-2</th>
<th>-1</th>
<th>0</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
</tr>
</thead>
<tbody>
<tr>
<td>CCI***</td>
<td>S&amp;P 500***</td>
<td>0.080</td>
<td>0.240</td>
<td>-0.080</td>
<td>0.111</td>
<td>0.537**</td>
<td>0.416*</td>
<td>-0.175</td>
<td>-0.054</td>
<td>-0.244</td>
<td>-0.174</td>
<td>0.022</td>
</tr>
<tr>
<td>CCI***</td>
<td>Business Week***</td>
<td>-0.048</td>
<td>-0.270</td>
<td>0.109</td>
<td>-0.18</td>
<td>0.467**</td>
<td>0.052</td>
<td>0.004</td>
<td>0.144</td>
<td>0.045</td>
<td>-0.042</td>
<td>-0.316*</td>
</tr>
<tr>
<td>Business Week***</td>
<td>S&amp;P 500***</td>
<td>-0.131</td>
<td>0.099</td>
<td>0.038</td>
<td>0.116</td>
<td>-0.074</td>
<td>0.377**</td>
<td>-0.126</td>
<td>0.031</td>
<td>-0.072</td>
<td>-0.445**</td>
<td>0.131</td>
</tr>
</tbody>
</table>

*Significant at p<.05.
**Significant at p<.01.
*** These series are first order differenced.

According to correlations shown in Table 8, a transfer function analysis has been conducted using those significant predictors. The results shown in Table 9 indicate that the tone of Business Week can explain 19.8 percent of variance of the CCI, and S&P 500 can explain 24.7 percent of variance of the CCI. Moreover, the CCI can explain 13.5 percent of variance of the tone of Business Week, and the tone of Business Week can explain 28.7 percent of variance of the S&P 500, which did not happen in the analysis of the overall 10 year data.
Table 9. Transfer function coefficients, total variance ($R^2$) explained, and incremental variance due to the predictors of the independent series (2001-2003)

<table>
<thead>
<tr>
<th>Dependent series</th>
<th>Independent series</th>
<th>Transfer function coefficient</th>
<th>Standard error of coefficient</th>
<th>Total $R^2$</th>
<th>Incremental $R^2$</th>
</tr>
</thead>
<tbody>
<tr>
<td>CCI***</td>
<td>Business Week***</td>
<td>6.759t-1***</td>
<td>2.404</td>
<td>0.198**</td>
<td>0.198**</td>
</tr>
<tr>
<td>Business Week***</td>
<td>CCI***</td>
<td>-.024t-5*</td>
<td>0.01</td>
<td>0.312*</td>
<td>0.135*</td>
</tr>
<tr>
<td>2 CCI***</td>
<td>S&amp;P 500***</td>
<td>0.033t</td>
<td>0.024</td>
<td>0.247*</td>
<td>0.247*</td>
</tr>
<tr>
<td>S&amp;P 500***</td>
<td>CCI***</td>
<td>2.103t</td>
<td>1.158</td>
<td>0.091</td>
<td>0.091</td>
</tr>
<tr>
<td>3 Business Week***</td>
<td>S&amp;P 500***</td>
<td>0.003t</td>
<td>0.002</td>
<td>0.256</td>
<td>0.079</td>
</tr>
<tr>
<td>S&amp;P 500***</td>
<td>Business Week***</td>
<td>29.190t-1*</td>
<td>15.394</td>
<td>0.287**</td>
<td>0.287**</td>
</tr>
</tbody>
</table>

*Significant at p<.05.
**Significant at p<.01.
*** These series are first order differenced.

Table 10 presents the results of the multivariate analysis based on the reduced model as below.

$$C_t = .044 S_t + .041 S_{t-1} + 6.011 B_{t-1} + a_t$$ (R-6)

Where $C$ is the CCI***, $S$ is S&P 500***, and $B$ is tone of Business Week***, $a_t$ is an error, $a_t \sim \text{nid}(0, 21.950)$.

The results show that the 18.5 percent of variance of the CCI is explained by the S&P 500, and 13.6 percent of variance of the CCI is explained by the tone of Business Week.

Table 10. Transfer function coefficients and incremental variance due to the predictors of the independent series in the multivariate analysis (2001 – 2003)

<table>
<thead>
<tr>
<th>Independent series</th>
<th>Transfer function coefficient</th>
<th>Standard error of coefficient</th>
<th>Total $R^2$</th>
<th>Incremental $R^2$</th>
</tr>
</thead>
<tbody>
<tr>
<td>1 S&amp;P500***</td>
<td>0.044t,</td>
<td>0.023</td>
<td>0.383*</td>
<td>0.185*</td>
</tr>
<tr>
<td></td>
<td>0.041t-1</td>
<td>0.022</td>
<td></td>
<td></td>
</tr>
<tr>
<td>2 Business Week***</td>
<td>6.011t-1*</td>
<td>2.341</td>
<td>0.383*</td>
<td>0.136*</td>
</tr>
</tbody>
</table>

*Significant at p<.05.
**Significant at p<.01.
*** These series are first order differenced.
Summary of the Findings

In general, the tone of *Business Week* is one of the causes of the CCI in terms of Granger causality. As was shown in Table 5, the economic reporting by media in one specific month can statistically explain 3.7 percent of the variance in the following month’s CCI. That is, the tone of *Business Week* in one month can predict the CCI in the following month. The Granger causality also presents in the reverse direction, which means the CCI can be a predictor of the tone of *Business Week*, since the CCI can explain 4.9 percent of variance of the tone of *Business Week*. However, that prediction is based upon a four-month lag in time, while the one, two and three-month lags failed to significantly predict *Business Week*. This suggests that this result might be spurious.

Second, the S&P 500 is a statistically significant predictor of the CCI. According to Table 5, the S&P 500 in the month 0, the month -1 and the month -2 explain 18.1 percent of variance of the CCI in the month 0. However, the CCI cannot be a predictor of the S&P 500 since the CCI can explain only 3 percent of variance of the CCI with no statistical significance.

In addition, after the analysis of the joint effect of both the S&P 500 and the tone of *Business Week* on the CCI, the results indicate that the S&P 500 can explain much more variance of the CCI than the tone of *Business Week* can (17.2% vs. 2.8%), which means the S&P 500 is a better predictor of the CCI than the tone of *Business Week* is.

During time periods of recessions and economic slowdowns, both the S&P 500 and the tone of *Business Week* can explain more percent of variance of the CCI (S&P 500: 24.7% vs. 18.1%; *Business Week*: 19.8% vs. 3.7%). Moreover, the S&P 500 is still a better predictor of the CCI than the tone of *Business Week* is (Bivariate analysis: 24.7% vs. 19.8%; Multivariate analysis: 18.5% vs. 13.6%). However, compared to that during normal times, the variance of
the CCI explained by the tone of *Business Week* increased during recessions, but the variance of the CCI explained by the S&P 500 is very close to that during normal times (*Business Week*: 2.8% vs. 13.6%; S&P 500: 17.2% vs. 18.5%). In addition, the CCI is a better predictor of the tone of *Business Week* and can explain 13.5% of variance of the CCI (13.5% vs. 4.9%), but this result remains doubtable since the effect comes from a five-month lag, which has been discussed above. The tone of *Business Week* becomes a significant predictor of the S&P 500 and can explain 28.7% of variance of the CCI, but this result remains doubtable since the effect comes from a four-month lag.
CHAPTER 5

CONCLUSIONS

Using Granger causal analysis and time series analysis, both of which have been applied to only a few studies of agenda setting effects, this study explores impacts of mass media coverage of the economy during normal times and recessions on the CCI. The findings of the analysis of data in normal times support the conclusion made by some previous studies as was discussed in Chapter 2 that economic reporting by mass media impacts consumer sentiment though the effect is not strong (Haller and Norpoth, 1997). That means economic reporting by media does have some second-level agenda-setting effect on consumer sentiment. The findings also support the idea that the real state of the economy impacts consumer sentiment, and its impact is much stronger than the impact of economic reporting. The reason for the weakness of the effect of media on public perception of the economy can be explained by some previous studies as was discussed in Chapter 2 that people’s perception of the economy is greatly shaped by what they personally observe and experience in their everyday lives (Linden, 1982; Behr & Iyengar, 1985) and the measures or indictors of economic condition such as inflation and unemployment (Haller and Norpoth, 1997).

In other words, economic reporting is a source for consumers seeking information of the real state of the economy, but mostly consumers receive their perception of the economy through their experience in their real lives, such as consumption, employment and incomes. One more possible interpretation is that the raw data of indicators of the economy are shown in media and are communicated to the public, but the effect of the data in media has been considered the effect of the real state of the economy in this case. These findings support the
first model shown in Figure 3 that the real state of the economy has more powerful effects on corresponding consumer sentiment than corresponding mass media coverage of the economy. 

During recessions and times of economic slowdowns, economic reporting of media has a more powerful effect on the CCI, which supports the idea from some previous research, as was discussed in chapter 2. Some reasons can explain this finding. For example, consumers update their expectations about the economy much more frequently during periods of high news coverage than during periods of low news coverage, while high news coverage of the economy is often experienced during and immediately after recessions (Doms and Morin, 2004). Wu, Stevenson, Chen and Guner (2002) suggested that individuals pay greater attention to economic news during times of economic slowdowns. Hester and Gibson (2003) suggested that people use personal experiences to make judgments whenever possible, but rely more on the media for issues out of their reach. The findings also suggest the idea that during economic slowdowns, mass media coverage of the economy is still not a better predictor of the CCI than the real state of the economy is, but its impact on the CCI increased compared to that during normal times, a result suggesting that consumer sentiment during economic slowdowns is shaped by media at a more significant level, or media have a powerful second-level agenda-setting effect on public opinion of the economy during recessions and times of economic slowdowns.

The results show that all three indicators – Business Week’s media influence, the CCI and the real state of the economy – tend to influence one another during times of recessions or economic slowdowns, while they do not during normal times. While this study cannot demonstrate why this occurs, it may be because consumers and media are more attentive to reports about the economy during adverse economic times, and thus are more affected. In the
case of the CCI effect on *Business Week*, as noted before, it is possible that this result might be due to chance, as there was a four or five-month lag between the CCI and its significant impact on *Business Week* coverage.

There are several options for more study. First, since this study only looked at *Business Week* headlines, which is a possible weakness, future studies can analyze the tone of the U.S. economy section in *Business Week* and other business publication through whole articles to see if different conclusions would be drawn. Second, future study can also explore effects of media other than print media to see if there are more powerful effects on public perception of the economy from electronic media, or from interpersonal communication.
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