

FORECASTING RECESSIONS: THE CONVERGENCE
OF INFORMATION AND PREDICTIVE
ANALYTICS

by

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A DISSERTATION

Submitted in partial fulfillment of the requirements for the
degree of Doctor of Philosophy in the College of
Communication and Information Sciences
in the Graduate School of
The University of Alabama

TUSCALOOSA, ALABAMA

2010

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ABSTRACT

The purpose of this study is to augment the predictive power of conventional recession-forecasting models by examining the interrelationships among macroeconomic indicators, government information sources and performance data of public companies. The latter two information sources are collectively referred to as institutional artifacts in this study. Evidence was sought of a predictive relationship between institutional artifacts and macroeconomic vulnerability, and the ensuing associations were modeled to provide long-range predictive insights that will serve as a forewarning of impending recessions.

The inclusion of public policy dialogue and corporate performance data as predictor variables in recession forecasting models not only extends the information paradigm associated with recession forecasting, but it also designates the unique contribution that this study makes to this area of research. To obtain a valid estimation of the predictive power of institutional artifacts, and to avoid falsely inflating their significance, the new variables were not modeled in isolation. Macroeconomic indicators published by government agencies and private institutions were retained as variables in the respective regression models used in this study.

The study found that the current ratio and total debt to assets ratio of Fortune 500 companies, and congressional hearings on economic matters significantly predicted the movement of the yield spread twelve months ahead. The study also found that the odds of a recession increase by 1.06 times, or 6%, for every one unit of increase in the number of congressional hearings held, holding other variables constant.

DEDICATION

This dissertation is dedicated to my brother, Steve Godfrey Subramany.

LIST OF ABBREVIATIONS AND SYMBOLS

<i>DF</i>	Degrees of Freedom: The number of independent data items in a statistical test
<i>F</i>	Fisher's ratio: Used to determine whether the independent variable reliably predicts the dependent variable
<i>p</i>	The probability associated with obtaining a test statistic that is at least as extreme as the one that was observed, assuming that the null hypothesis is true.
<i>R-squared</i>	Coefficient of determination: A statistical measure of the proportion of variability accounted for by the model
<i>T</i>	A measure of the statistical significance of the independent variable in explaining the dependent variable
<	Less than

ACKNOWLEDGEMENTS

I am pleased to have this opportunity to thank my colleagues, friends and faculty who have assisted me with this research project. I am deeply indebted to my dissertation chair, Dr. Danny P. Wallace, for his expert guidance as I negotiated the doctoral program and the dissertation process. Thank you for generously sharing your experience and wisdom with me. I value your steadfast support and kind encouragement, as well as your attention to detail. I would also like to express my sincere gratitude to my dissertation committee members, Drs. Arthur Allaway, Elizabeth Aversa, Jason Black, and Stephen Borrelli. Thank you for your invaluable input, inspiring questions, and support for both my dissertation and academic progress. Thank you also for your extreme flexibility and willingness to accommodate my timeline. A special thank you to Dr. Aversa for making this project possible – your leadership inspires me.

Much gratitude to my extraordinary family in South Africa for your kindness, support and encouragement. And to my exceptional friends, a very special thank you. Tony Via, your contribution to this project was invaluable. Dr. Mary Meares, Dr. Chapman Greer, Melissa Koener, Daniel Tackett, Morgan Higgins, Asya Cooley and Shannon Kee – how could I possibly thank you enough? Skye Cooley, thank you for keeping me in shape both mentally and physically. And finally, to my A&F for sharing my angst and my highs, for keeping me grounded, and for being my biggest fan – I applaud you! Above all, I thank God, without whom none of this would have been possible.

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Preface

The purpose of this study is to devise a predictive model that forecasts recessions at long-range by leveraging the interrelationships among seemingly disparate data. Specifically, this study examines macroeconomic indicators, government records and performance data of public companies; identifies interesting subsets of observations and possible associations between these attributes and the dependent variable; and then uses the resulting associations to build the predictive model.

The Sveriges Riksbank Prize in Economic Sciences in Memory of Alfred Nobel (the Nobel prize for economics) in 2001 honored three recipients for work done under the banner “Information for the Public” (para. 1). As a preamble to the official announcement of the winners, the Royal Swedish Academy of Sciences rendered the statement:

Why are interest rates often excessively high on local lending markets in Third World countries? Why do people who want to buy a good used car turn to a dealer rather than a private seller? Why does a firm pay dividends even if they are taxed more heavily than capital gains? Why is it advantageous for insurance companies to offer clients a menu of contracts where higher deductibles can be exchanged for lower premiums? Why do rich landowners not bear the entire harvest risk in contracts with poor tenants? These questions exemplify familiar – but seemingly different – phenomena, each of which has posed a challenge to economic theory. This year's Laureates proposed a common explanation and extended the theory when they augmented the theory with the realistic assumption of asymmetric information: agents on one side of the market have much better information than those on the other side. Borrowers know more than the lender about their repayment prospects; the seller knows more than buyers about the quality of his car; the CEO and the board know more than the shareholders about the profitability of the firm; policyholders know more than the insurance company about their accident risk; and tenants know more than the landowner about their work effort and harvesting conditions (Royal Swedish Academy of Sciences, 2001).

The information continuum facilitates economic transactions and empowers the various agents impacted by such transactions. The excerpt underscores a fundamental construct: information is the driver of the economic environment. In each instance, even though agents on one side of the market have better information than those on the other, expedient leveraging of this information will effectively facilitate the respective transaction, ultimately empowering the agents on both sides.

When it comes to economic information, institutions are of critical importance (Eggertsson, 2006). Both public and private institutions collectively capture and process vast quantities of economic data, and are often armed with much better information than those on the other side. Effectively leveraging this data may create a better-informed, empowered public who can navigate their way through anomalous economic situations.

Of interest in this study is the data generated by public institutions. Specifically, the study is concerned with extracting information from data originated by the United States government and publicly held corporations in the United States. It is argued that judicious mining of this data may reveal trends, patterns or relationships among the data that may not be readily apparent. This information may then be used to develop predictive models that indicate the likelihood of a particular event or behavior occurring.

Ultimately, this study is about extracting information from historical and transactional data and using it to predict future economic trends and behavior. It focuses on the unification of different sources of knowledge by harnessing the core elements of competitive intelligence and knowledge management processes. Competitive intelligence processes inform the gathering of usable knowledge about the economic environment, while knowledge management processes

inform the efficient usage of the information gathered and how it *can be best positioned* for effective risk mitigation.

Chapter One

Introduction

Adequate forewarning of an imminent recession can significantly limit its severity and mitigate the gravity of its impact. However, conventional methods of forecasting recessions have not met with much overall success historically. These methods are particularly ineffective when it comes to long-range forecasting (greater than one year). The purpose of this study is to augment the predictive power of conventional recession-forecasting models by examining the interrelationships among macroeconomic indicators, government information sources and performance data of public companies. Government information and corporate data are collectively referred to as institutional artifacts in this study. The study sought evidence of a predictive relationship between institutional artifacts and macroeconomic vulnerability, and then modeled these possible associations to provide long-range predictive insights that will serve as a forewarning of impending recessions.

In September 1929 Secretary of Treasury, Andrew W. Mellon declared, "There is no cause to worry. The high tide of prosperity will continue" (Thornton, 2004, para.11). Mellon's optimism was proven unfounded in October 1929, when the crash of the U.S. stock market announced the Great Depression.

In February 2008 the White House predicted that the economy would escape a recession and that unemployment would remain low that year. Edward P. Lazear, chairman of the White House Council of Economic Advisers remarked: "I don't think we are in a recession right now, and we are not forecasting a recession" (Andrews, 2008, para. 2). By December 2008, the

National Bureau of Economic Research (NBER), the organization that determines the official dates for the beginning and end of a recession, determined that the U.S. had been in a recession since December 2007.

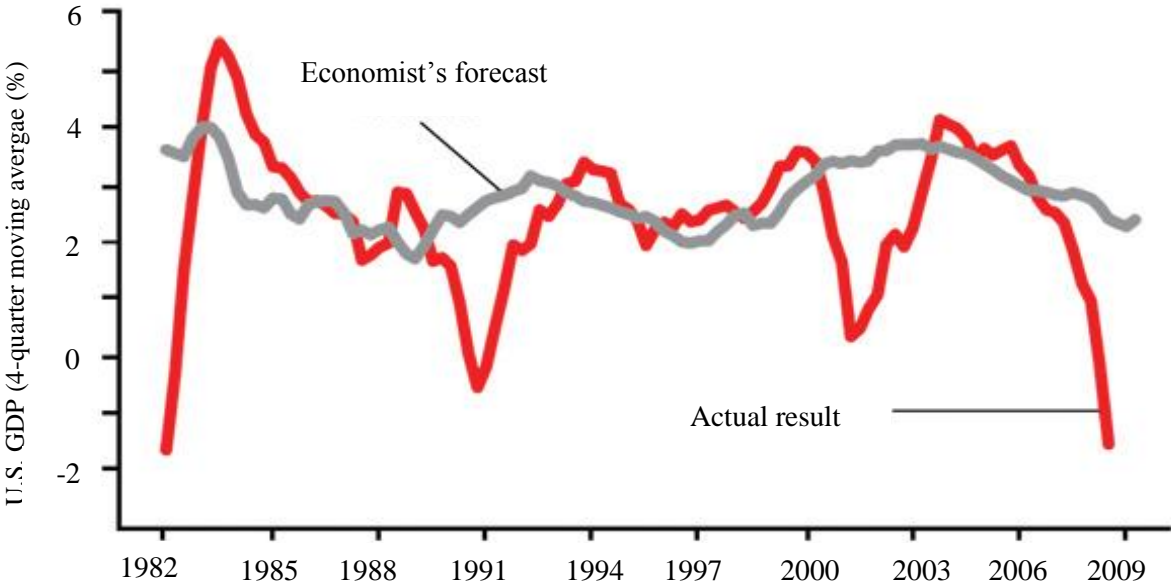
The preceding accounts reveal substantial similarities. The worst of their respective eras, both recessions unleashed financial and social chaos across the United States. A beleaguered economy, double-digit unemployment rates, and the collapse of the financial sector are only a few of the negative outcomes that emerged. Surprisingly, neither event appeared to have merited any worry or concern from experts in the period immediately preceding it. In both cases there was a manifest failure to foresee, or at least to acknowledge, that the economy was entering a period of substantial weakness.

The United States has been affected by a number of recessions of varying magnitudes and intensities over the last three centuries. The National Bureau of Economic Research has identified thirty-two U.S. recessions since the mid-1850s. Of these, ten recessions have occurred since 1945, averaging approximately one recession every six years. Given the prolific frequency of these economic contractions, it is not unreasonable to assume that a significant amount of intelligence would have accrued over time to inform valid predictions and forecasts about the economy. Unfortunately, the track record of forecasters fails to support this assumption. Predictions concerning the severity (or duration and depth) of economic contractions have historically been largely inaccurate. In 2002 the International Monetary Fund conducted a study of consensus forecasts that were made in advance of sixty different national recessions. A consensus forecast is an average of all of the individual predictions made by a large group of economists. The study found that in 97% of the cases the economists did not predict the contraction a year in advance. On those occasions when successful predictions were made, the

severities of the respective recessions were grossly underestimated (Loungani, 2002). Lahiri & Moore (1991) found that in both the 1973-75 recession and the 1981-82 recession, forecasters failed to predict that these recessions would be the longest of the post-world war period, up to that point.

In addition to having little success with predicting the severities of recessions, forecasting models have sometimes predicted recessions that never actually materialized (Makridakis, 1982). Miller (2007) contended that the astonishing complexity of the U.S. economy and the fact that it is impacted by so many variables makes it impossible for economists to predict recessions. He goes on to suggest that economists can't even say for certain one is under way until months after it has begun. Montier (2009) validated these claims in a study which found that significant variance exists between actual economic performance and economists' forecasts. Figure 1 summarizes his findings.

Figure 1. Variance between actual economic performance and economists' forecast



Note. Adapted from Montier, J. (2009, February 24). The tao of investing: The ten tenets of my investment creed. *World Global Strategy*. Retrieved from <http://www.scribd.com/doc/27599172/James-Montier-10-Tenets-of-Investing>. Copyright 2009 by SG Global.

Montier analyzed economists' prediction of Gross Domestic Product (GDP), a macroeconomic indicator, against actual performance of GDP. The area between the line showing economists' forecasts and the line showing actual results highlights the extent of the discrepancy between forecasted GDP and actual GDP. Between 1989 and 1991, for example, economists forecasted that GDP will trend upwards, but actual GDP trended sharply downward. Similarly, between 2000 and 2001, economists forecasted a stable to increasing growth in GDP, but actual GDP showed a severe decline.

Not having an early warning system that alerts the public and private sector to an imminent severe contraction can have catastrophic results. The Great Depression and the 2007 recession are cases in point. In both instances, the erroneous, misleading forecasts of the economy in the months immediately preceding the recession probably contributed to the severity of the recession. Adequate forewarning could have potentially encouraged proactive measures that may have mitigated the gravity of the outcomes. This apparent failure on the part of forecasters to anticipate the depth and duration of a recession reasonably in advance of its onset, and the demonstrated variance between actual and forecasted results in figure 1 provide compelling evidence of potential limitations in the data and methods leveraged for computing forecasts.

According to the United Nations Department of Economic and Social Affairs, economic contractions are normally visible in real GDP, real income, employment, industrial production, and wholesale-retail sales, all of which are macroeconomic indicators (United Nations, 2008). This is consistent with evidence in the literature which shows that current recession forecasting models favor macroeconomic indicators as predictor variables (Estrella and Mishkin, 1995; Zarnowitz & Moore, 1982; Filardo, 2004; Keen (1983). Given the dissonant relationship

between forecasted results and actual results, a concern about potential limitations in the predictive power of macroeconomic indicators is brought to light.

Problem Statement

The preceding discussion delineates three essential problems confronting recession forecasting:

1. The difficulty of predicting recessions with certainty
2. The difficulty of providing long range predictions of recessions
3. The difficulty of predicting the depth and duration of a recession

This investigation is concerned with addressing the first two problems. The difficulty of making definitive predictions reasonably ahead of a recession's onset is probably attributable to a range of factors. This study argues that one such factor is the issue that present forecasting models exclude variables that are not classified as macroeconomic indicators.

It is a prediction of this study that while macroeconomic vulnerability is a function of real GDP, real income, employment, industrial production, wholesale-retail sales, stock market performance, and the yield curve, institutional artifacts potentially play an important role in enhancing the collective predictive power of these variables. Within the context of this study, institutional artifacts refer to the records of public corporations as well as the government and its agencies. Consequently, this study includes government policymaking records and public company records as variables in forecasting models. Specifically, these variables incorporate:

1. Presidential executive orders
2. Congressional hearings
3. Public company performance data

The study does not suggest that these variables supplant macroeconomic models and judgmental forecasts currently in use. Instead, because of the dubious track record of these mechanisms as they currently exist, the study asserts that the identified variables offer value in terms of supplementing the existing data employed in current forecasting models.

Research Questions

In order to test whether the inclusion of these datasets augment the predictive power of conventional forecasting models, two research questions were examined:

1. Is there evidence of a predictive relationship between institutional artifacts and macroeconomic vulnerability?
2. Does the relationship between institutional artifacts and macroeconomic vulnerability provide any predictor variables that may serve as a long-range signaling device for a recession?

Scope of this Study

This study explores the principle that an analysis of the economic, political, and industrial environment for the three years preceding a major contraction offers predictive insight of the approaching contraction. Makridakis (1982) summarized the characteristics of all recessions that afflicted the United States over a period of 125 years (1854-1975). Based on this summary, he posited, “It can be seen from this illustration that the ‘average’ business cycle has a duration of little more than four years” (p. 48). Following from this, if the fourth year is the contraction year in the cycle, the preceding three years may potentially offer a logical data horizon for analysis. Specifically, this study analyzes the economic-centric intelligence gathered in the three years leading up to four major recessions in the last four decades. One recession from each decade is represented, as identified below:

- The recession of 1973, which was the fourth worst recession in U.S. history
- The recession of 1981, which was the third worst recession in U.S. history
- The recession of 1990, which was a comparatively mild recession
- The recession of 2007 - referred to as the “The Great Recession,” it is the second worst recession in U.S. history

A total of twelve years of data were analyzed. For each year presidential executive orders, congressional committee hearings, Fortune 500 company performance data, and macroeconomic indicators were analyzed. The representative sample population for the company analysis includes a list of twenty companies that have consistently appeared on the Fortune 500 list for the respective periods of analysis. A systematic sampling technique was employed to extract the sample. The sample contains a broad representation of industries, including companies that engage in a diverse array of operational activities such as healthcare services, biomedical research, oil and gas refining, information technology services, industrial goods production, and consumer goods production. The companies included in the sample were:

1. Abbott Labs
2. Alcoa
3. Archer Daniels Midland
4. Cummins
5. Coca-Cola
6. Crown Holdings
7. DuPont
8. Exxon Mobile
9. Hormel Foods

10. Goodrich
11. Honeywell International
12. Kellogg
13. Navistar International
14. Pfizer
15. Raytheon
16. Sunoco
17. Unisys
18. Becton Dickson
19. Caterpillar
20. ConAgra Foods

Unique Contribution of this Study

The subject of business cycles is addressed extensively in the social sciences literature. A prominent research agenda within this sphere is the study of economic recessions. These studies are primarily centered on two areas: (1) causes of recessions, and (2) forecasting recessions. Knoop (2004) argues that “after more than 200 years of debate there is still no general agreement about what causes recessions” (p. 4). He attributes this to the fact that economists persistently employ multiple competing models of business cycles. He comments further that there is a “large disconnect between the models used by academics and those used by private sector economists” (p. 4).

While it is not the goal of this study to determine the causes of recessions, Knoop’s comments highlight a salient challenge that has wide transferability into other areas of study relating to this subject, including the area of recession forecastability. As highlighted earlier,

agreement on the ability of forecasters to correctly predict the timing of recessions well in advance of its occurrence is elusive (Lahiri & Moore, 1991). This makes it difficult for steps to be taken to mitigate the impact of an oncoming recession. As experienced in other areas of study relating to recessions, a large disconnect prevails between the models used by academics and those used by private sector economists. However, when it comes to the data and metrics used in these models, greater consensus emerges. The models used by both the private and academic sector forecasters primarily utilize economic data and economic metrics to compute their analyses. Different economic models may analyze different data series or different metrics, but ultimately, the data falls within the broad classification of “economic” data, and more specifically, macroeconomic data.

The unique contribution of this study is that it extends the boundaries of the conventional methodological approaches to forecasting by including government and corporate institutional data as predictor variables. Specifically, it engages three datasets:

1. Presidential executive orders addressing economic issues
2. Congressional committee hearings addressing economic issues
3. Productive efficiency and profitability data of a sample of Fortune 500 companies

It is not the goal of this study to reject the models employed by forecasters currently and historically. Nor is it the goal of this study to provide a definitive forecasting model to replace the models currently used. This study examined the potential of developing a more comprehensive predictive model which factored in three additional data series that have yet to be correlated with macroeconomic data. It was envisioned that this would produce new predictor variables that exhibited coincident timing with, and cluster around business cycle downturns. This instrument is intended to serve as an early warning system of the U.S.’s economic fragility

at a given point in time, thereby helping policymakers and other stakeholders to proactively take steps to reduce the depth and duration of a contraction.

Limitations of the Study

1. This study uses logistic-regression to model the data. The model for logistic-regression analysis assumes that the outcome variable, R, is binary (categorical). This means that there are only two possible outcomes, i.e., “Yes” or “No.” Because the probability of a response is being predicted, R takes on the value of 1 when the outcome is positive (or a success) and 0 when the outcome is negative (or a failure).

Implicit in this approach are two limitations:

- While the occurrence of recessions is predicted, this iteration of the model does not prognosticate depths and durations of such recessions.
- This iteration of the model does not assess causality.

Despite these limitations, this phase of the predictive model is an important beginning because it attempts to significantly increase the range of the forecast. The next phase of the model will address depth and duration as well the causal dynamics of recessions.

2. Data for the congressional hearings and presidential executive orders were extracted from The Policy Agendas Project, an online resource portal. This resource is unique in that it is not just a repository for institutional data, but that the data has already been coded by expert coders. The coding frame is very comprehensive and the coding categories are mutually exclusive. From the outset, rigorous coding and reliability standards were imposed in the coding process. The stringent reliability measures and the significantly high reliability scores ensure a dataset with documented reliability.

These datasets have been used extensively in important research projects (e.g., Mortensen, 2009; Agnone, 2007; Purpura & Hillard, 2006; Wilkerson, Feeley, Schiereck & Sue, 1999). A latent limitation of using a pre-coded dataset is the researcher's lack of direct involvement in the coding process and the development of the coding schema. While it does not expose the study to any manifest threat in terms of its validity, it does narrow the range of insight of the researcher into the coding process.

Definition of Key Terms and Concepts Used in this Study

- *Advanced Monthly Sales – Retail Trade & Food Services*: The business sales and inventories statistic measures trends in inventory build-up. If inventories are accumulating rapidly, it may be indicative of contraction in business growth, while declining inventories signal an increase in business growth.
- *Capacity Utilization*: Capacity utilization refers to a measure of the industrial capacity of factories, mines and utilities, and how much of it is being used. The report is published monthly by the U.S. Federal Reserve.
- *Congressional Committee Hearings*: A congressional committee hearing is a meeting or session of a Senate, House, Joint, or Special Committee of Congress to obtain information and opinions on proposed legislation, conduct an investigation, evaluate or oversee the activities of a government department, or the implementation of a Federal law. Hearings may also be purely exploratory in nature, providing testimony and data about topics of current interest (GPOAccess, 2010).
- *Consumer Price Index (CPI)*: The CPI is a price index that is determined using a fixed basket of goods that are representative of what a typical consumer purchases

each month. The inflation rate is computed by measuring the increase in the CPI over a specific period. The CPI is published by the Bureau of Labor Statistics and is an important economic indicator.

- *Contraction*: A contraction is a period of significant decline in the level of economic activity
- *Cyclical Indicators*: Cyclical indicators are classified into three categories - leading, coincident, and lagging. Leading indicators are indicators that shift ahead of the business cycle, i.e., they will trend down before the business cycle enters a contraction phase, and they will trend up before the business cycle enters a period of expansion. Examples of leading indicators include new manufacturing orders, consumer sentiment, housing permits, and stock prices. Coincident indicators measure aggregate economic activity and move in tandem with the business cycle. Examples of coincident indicators include production, personal income, and manufacturing and trade sales. Lagging indicators are reactive indicators that shift after the business cycle has shifted. For example, they will trend downward after the business cycle has entered a contraction phase. Examples of lagging indicators include unemployment rate, interest rate, and labor cost per unit of output.
- *Executive Orders*: Executive orders are official documents through which the president of the United States manages the operational activities of the government (The National Archives.gov, 2010)
- *Expansion*: An expansion period of increased growth in the level of economic activity

- *Fiscal Policy*: Fiscal policies refer to policies executed by the government to keep the economy balanced. By adjusting the levels and allocations of taxes and government spending, the government can stimulate the economy or slow it down.
- *Fortune 500 Company*: A Fortune 500 company is a company that appears on *Fortune* magazine's list of the 500 most profitable public corporations in the United States, based on gross revenues. Fortune 500 companies are regarded as the bastions of the economy.
- *Gross Domestic Product (GDP)*: The GDP is the total market value of the goods and services produced by a country during a specific period of time.
- *Gross National Product*: The GNP is the total value of all goods and services produced in the nation as well as that produced by that nation's companies whose production facilities are outside that nation's borders.
- *Housing Starts*: A housing start is defined as beginning the foundation of a new home. The U.S. Census Bureau publishes this indicator monthly in the *New Residential Construction Report*. Housing starts normally increase at the beginning of an expansion cycle, hence the importance of this indicator.
- *Industrial Production*: This indicator is a measure of the change in the production of factories, mines and utility companies, and is published monthly by the U.S. Federal Reserve.
- *Institutional Records*: Within the context of this study, institutional records include all documents or records that are created in connection with the activities and business of the federal government and publicly traded companies. These records

- provide information and evidence concerning policies, decisions, procedures, functions, financial performance, or other activities of the institution.
- *Leading Economic Index*: This index is determined from the values of ten key economic variables, and is calculated by The Conference Board (see The Conference Board in next section). The ten key variables are: Average weekly hours, manufacturing; Average weekly initial claims for unemployment insurance; Manufacturers' new orders, consumer goods and materials; Index of supplier deliveries – vendor performance; Manufacturers' new orders, nondefense capital goods; Building permits (new private housing units); Stock prices, 500 common stocks; Money supply (M2); Interest rate spread (10-year Treasury bonds less federal funds); and Index of consumer expectations.
 - *M2 Money Supply*: The M2 money supply is a measure of the total amount of money available in an economy at a particular point in time. It is an important instrument for controlling inflation.
 - *Macroeconomic Variables*: Macroeconomic variables are phenomena that have economy-wide impacts, such as the unemployment rate, gross domestic product, inflation, and price levels.
 - *Macroeconomics*: Macroeconomics is the study of economic factors as well as movements and trends that affect the economy as a whole.
 - *Macroeconomy*: The macroeconomy refers to the economy as a whole. The focus is not on a specific firm or industry.
 - *Monetary Policy*: Monetary policy refers to policies executed by the Federal Reserve to control the money supply. By controlling the availability of spending money to

firms and consumers, the Federal Reserve can keep inflation and the economy in check.

- *Nonfarm Payroll Employment*: This is a monthly estimate of the number of payroll jobs at all non-farm businesses and government agencies. This report also includes data on average hourly and weekly earnings as well as the average number of work week hours. The report is published by the Bureau of Labor Statistics and is an important economic indicator.
- *Retail Sales*: This is a measure of all retail activity in the U.S. It effectively measures consumer spending. The report is published monthly by the U.S. Department of Commerce.
- *S&P 500 Stock Index*: This index is compiled by Standard and Poor. It includes 500 leading stocks in leading industries of the U.S. economy and its performance is deemed to be representative of the U.S. stock market as a whole.
- *Yield on 10-year Treasury Note*: Treasury bonds are issued by the United States Treasury. A 10-year Treasury note represents debt owed by the United States Treasury to the public. A 10-year Treasury note is issued with a stated rate of interest (for example 3% of the note's face value). Every year holders of this note receive the stated rate of interest from the Treasury, which is paid semi-annually. After ten years, the note matures and the owner is paid the face value. The percentage of that total payment that exceeds the 10-year Treasury Note's market price, annualized, is called the yield (Investorglossary, 2010)

Organizations, Agencies and Committees Referenced in this Study

- *Business Cycle Dating Committee*: This is a committee of the NBER (see NBER) that determines the dates of business cycles using, not only GDP, but a range of indicators.
- *Congressional Committee*: Congressional Committees are established by Congress to divide responsibility for its many tasks. Congressional committees play a pivotal role in the legislative process. Once a bill comes to the floor of the House or Senate, the committee whose jurisdiction it falls under is usually responsible for guiding it through debate and securing its passage. There are approximately 200 Congressional committees and subcommittees in the House and Senate.
- *National Bureau of Economic Research (NBER)*: The National Bureau of Economic Research is a private, nonprofit, nonpartisan research organization dedicated to promoting a greater understanding of how the economy works. Sixteen of the 31 American Nobel Prize winners in Economics and six of the past Chairmen of the President's Council of Economic Advisers have been researchers at the NBER (NBER, 2010). The NBER is considered the official arbiter of recessions in the nation, and they are responsible for declaring the start and end dates of recessions.
- *The Conference Board*: The Conference Board is a non-profit global business organization that creates and disseminates knowledge about the marketplace. They conduct research, convene conferences, make forecasts, assess trends, and publish information and analysis. The organization produces Leading Economic Indicators for the United States, and nine other countries. It also produces the Consumer

Confidence Index. Both of these metrics are employed in this study (The Conference Board, 2010).

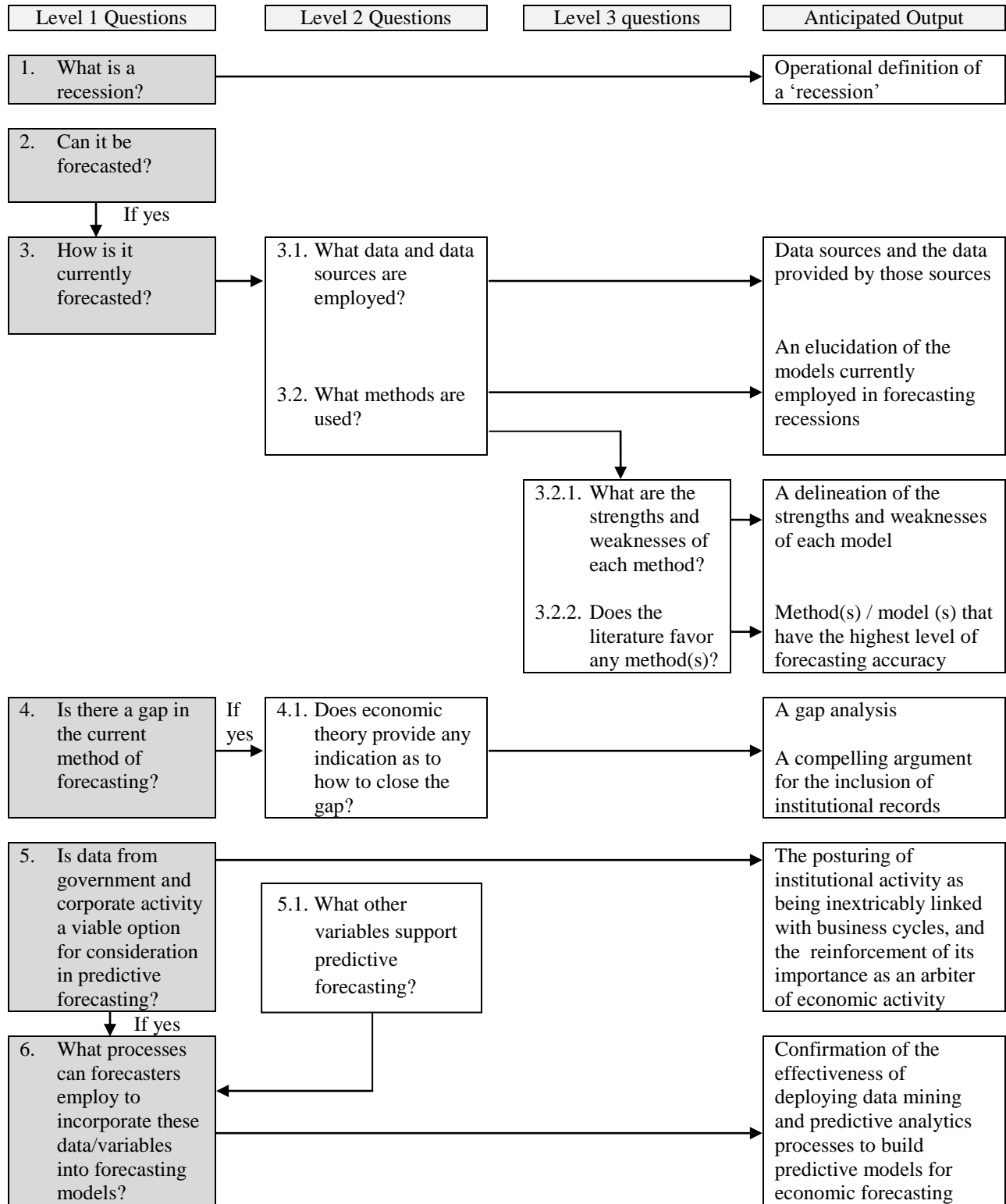
Chapter Two

Review of the Literature

The purpose of the study is to augment the predictive power of conventional recession-forecasting models by examining the interrelationships among macroeconomic indicators, government information sources, and performance data of public companies. Government information and corporate data are collectively referred to as institutional artifacts in this study. The study sought evidence of a predictive relationship between institutional artifacts and macroeconomic vulnerability, and then modeled these possible associations to provide long-range predictive insights to serve as a forewarning of impending recessions.

This chapter examines five separate bodies of research: (1) the anatomy of a recession, (2) the current state of predictive forecasting and the methods used to forecast recessions, (3) macroeconomic theories of business cycles and forecasting, (4) the relevance of institutional activity in the context of predictive forecasting, and (5) the use of data mining and predictive modeling in the advancement of economic forecasting. Figure 1 provides a conceptual representation of the overarching rationale that guides the structure of this literature review.

Figure 2. Concept map of the overarching rationale guiding the structure of the literature review



The first section of the literature review seeks to establish a broad working definition of a recession by examining the common tenets that compose and designate its characteristics and behavior in the literature. An accurate, thorough, historically correct definition of a recession is fundamental to understanding how it can be effectively forecasted. As a precursor to establishing a definition of a recession, a summary explication of business cycles is provided.

Forecasting of recessions has earned a questionable reputation. The second section of the review evaluates the extent to which economists and other forecasters have been successful in predicting the timing and depth of recessions by examining empirical research in this area. It goes on to examine the current state of macroeconomic forecasting, and highlights the empirical regularities and irregularities with the indicators and methods used by forecasters to predict recessions. Several studies document a weakening link in the relationship between methods used to forecast economic activity and actual economic activity. A systematic evaluation of the economic models used to forecast recessions is conducted in order to assess whether they have meaningful forecasting ability. Also included in this section is an examination of the data conventionally used in forecasting exercises and the sources from which they originate.

Macroeconomic theories of business cycles and forecasting provide two linkages: (1) they provide strong support for the inclusion of institutional activity as predictor variables in forecasting models, and (2) they identify those economic indicators and variables that have strong predictive power. In the third section of the review, three primary economic models are presented: the Classical model, the Keynesian model, and the Rational Expectations model. Provided for each model is a brief historical context, the basic theory behind it, a description of how the model relates to business cycle forecasting, and how it positions institutional activity as a credible predictor variable for forecasting recessions.

The fourth section of the review contextualizes all the variables that are being analyzed in this study. It starts by validating the notion that institutional artifacts may provide useful information that could potentially enhance the rigor of economic forecasting. Three different types of institutional artifacts are presented: presidential Executive Orders, Congressional Committee Hearings, and Performance data of Fortune 500 companies. The literature establishes all three components as being highly sensitive to economic activity. Next, the section goes on to contextualize the remaining variables that inform this study. These include macroeconomic indicators (a traditional mainstay of economic forecasting models), and the yield curve.

The final section of the review examines studies that have employed data mining and predictive modeling techniques to optimize business and economic forecasting. The common finding among these studies was that, over time, data mining processes and predictive analytics techniques have been successfully leveraged to build models that effectively predict a specific economic outcome which is a goal that this study endeavors to accomplish

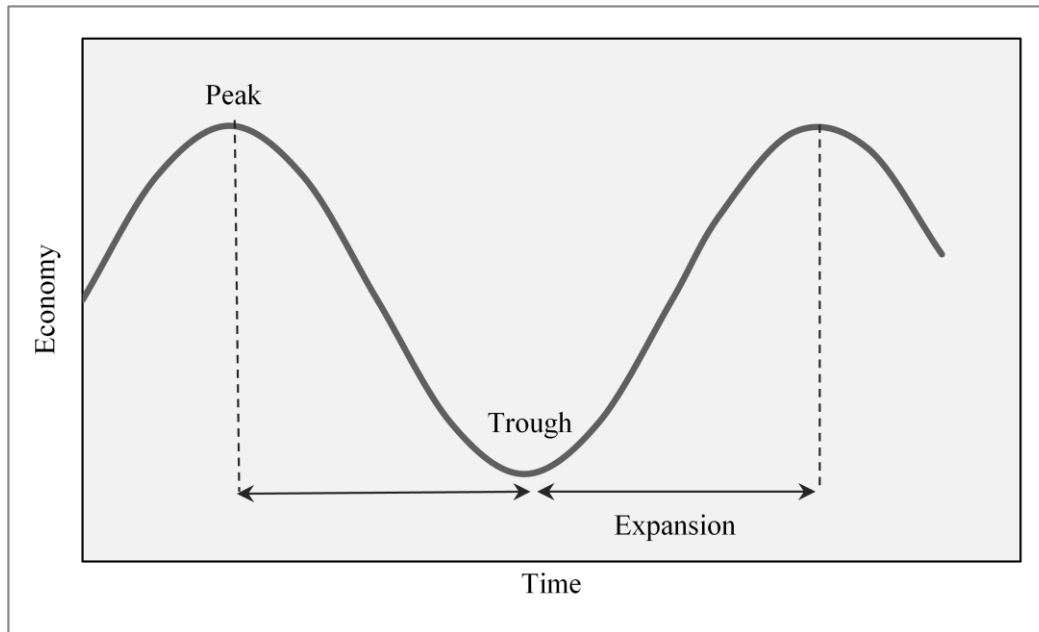
What is a Recession?

Business cycles. In order to understand what a recession is, it is necessary to understand business cycles and how they align with the structures and institutions of the economy.

According to Parkin and Bade (2001), the business cycle is the periodic but irregular up-and-down movements in economic activity, measured by fluctuations in real gross domestic product (GDP) and other macroeconomic variables. Examples of macroeconomic variables include economic output, employment and unemployment, inflation, interest rates, and productivity. The business cycle is characterized by four stages: contractions, expansions, troughs, and peaks. Contractions represent a decline in the pace of economic activity, while expansions represent a period of increased business activity. Peaks represent the highest point of continuous expansion,

while troughs represent the lowest point of continuous decline in economic activity. Figure 2 provides a diagrammatic representation of business cycles:

Figure 3. Different phases of a business cycle



The business cycle is not a phenomenon regulated by a mathematical law (Hansen, 1964, p. 281); it is largely unpredictable and of varying amplitude and length. A recession typically occurs when the decline in the pace of economic activity is particularly steep. Recessions are thus associated with the contraction stage of the business cycle.

Recessions. In their seminal work on business cycles, Burns and Mitchell (1946) submitted that a recession is a significantly lengthy decline in economic activity that broadly affects various sectors of the economy. This definition, which is widely quoted in the literature, is consistent with the view taken in contemporary business cycle analysis, where the “3 D’s” definition of a recession is emphasized: *duration*, *depth* and *diffusion*. For a contraction to be confirmed as a recession it must be sufficiently long (*duration*), it must result in a substantial decline in economic activity (*depth*), and it must involve multiple or all economic sectors rather

than simply reflecting a decline in a single economic sector or region (*diffusion*) (Stock and Watson, 1992). Both definitions, in an attempt to be all encompassing, emerge as somewhat vague and lend themselves to all manner of subjective interpretation.

The conventional contemporary definition of a recession is that it is denoted by two consecutive quarters of negative GDP growth (Burtini, 2008, Learner, 2008). In other words, for a period of contraction to be designated a recession, the market value of a country's overall output of goods and services, excluding net income from abroad, must have declined for two successive quarters. The basic formula to calculate GDP is:

$$Y = C + I + G + E, \text{ where}$$

$$Y = \text{GDP}$$

$$C = \text{Consumer Spending}$$

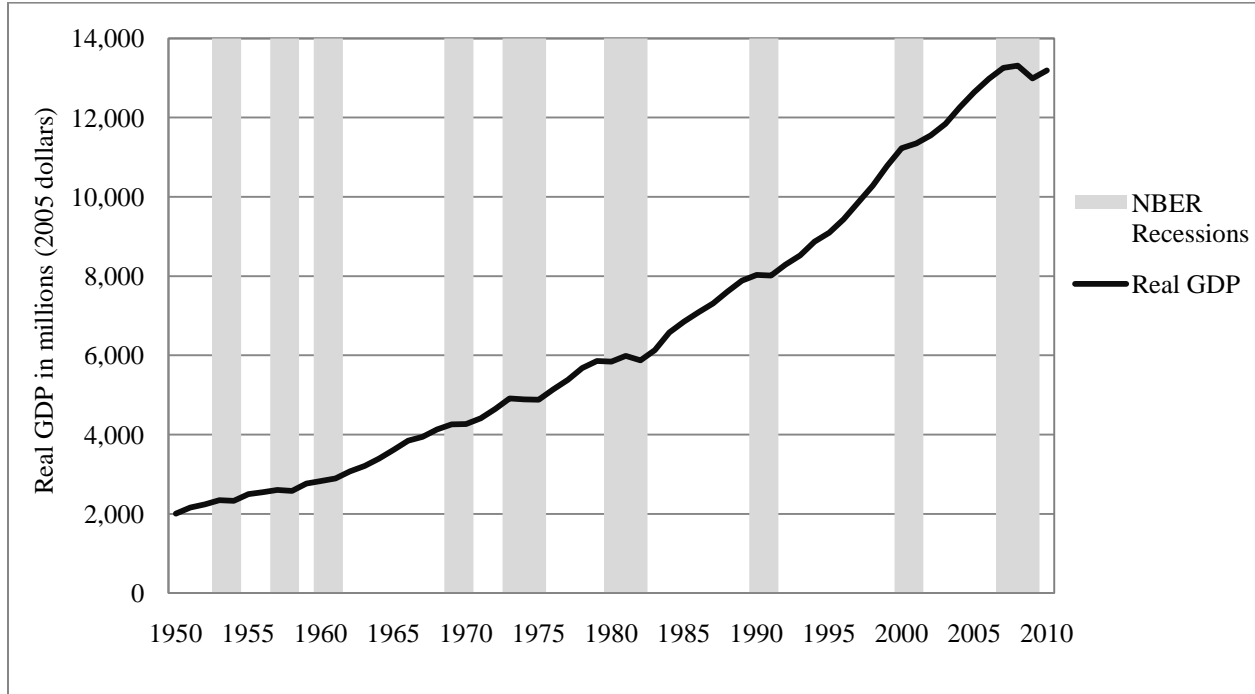
$$I = \text{Investment made by industry}$$

$$G = \text{Government Spending}$$

$$E = \text{Exports minus Imports}$$

While this definition is accepted globally, many economists question its effectiveness in defining a recession. Despite the fact that GDP is one of the broadest measures of economic activity (Filardo, 1991), they argue that it fails to consider other pertinent economic variables such as unemployment rates and consumer sentiment. This argument is noticeably tenable when the individual components of the equation are examined. Figure 3, below, corroborates their skepticism. The curve is fairly smooth, except for the last recession. No significant negative changes in the path of the curve are noticeable in the period preceding the respective recessions (which are indicated as shaded grey bars) otherwise, bringing into question its legitimacy as the variable used to define recessions.

Figure 4. Gross Domestic Product (GDP) mapped against NBER Recessions



The Business Cycle Dating Committee of the National Bureau of Economic Research (NBER), the U.S. entity that provides the start and end dates of recessions, also refutes the premise that real GDP is the definitive indicator of an economic recession. The basis for this assessment lies in the premises that, (1) GDP is only measured quarterly rather than monthly, and (2) the GDP number is subject to continuing revisions. The second premise requires further explication. The GDP numbers released by the U.S. government are revised when more complete data are received. Unfortunately, these data updates may often be received years later in the form of tax returns and via other avenues. As a result, substantial anomalies often exist between what was reported at a specific time and the final, corrected dataset (Harrison, 2009). Thus, designating a recession based on the initial dataset may potentially be premature.

Another economic indicator that may be variable to consider when determining the nature of a recession, is the real gross national product (GNP) (Moore, 1993). However, basing the definition of a recession on changes in the real GNP holds its own set of challenges. The GNP is

calculated by computing the value of income earned from overseas investments by residents, minus income earned within the domestic economy by overseas residents, and adding it to the GDP (Soubotina, 2004). Changes in real GNP are not always in sync with the official NBER business cycle chronology. Whereas real GNP should rise during expansionary cycles and decline during recessionary cycles, over the past sixty years real GNP has actually *declined* in eleven quarters classified as expansions, and has *risen* in five quarters during recessions (Lahiri & Moore, 1991). Thus, defining a recession based on GNP data may be problematic.

To alleviate these challenges, and provide a more comprehensive explanation of what a recession is, the NBER proposed that “a recession is a significant decline in activity spread across the economy, lasting more than a few months, visible in industrial production, employment, real income, and wholesale-retail trade” (para. 2). The NBER proposed four indicators as being the most important measures taken into consideration in determining business cycle chronology: (1) employment, (2) personal income less transfer payments, (3) the volume of sales of the manufacturing and sectors, and (4) industrial production. According to the NBER, the broadest monthly indicator in the entire economy is employment (NBER, 2001).

The preceding discussion draws attention to the dissident views in the literature surrounding the definition of a recession. Regardless of which perspective is adopted, the NBER, as the bona fide arbiter of recessions in the U.S., is responsible for making the official declaration of the start and end dates of a recession. Thus, driven by pragmatic concerns, this study embraces the broad definition of a recession of the Business Cycle Dating Committee of the NBER. Even though, as pointed out earlier, the definition lacks specificity in terms of the length of an observed decline, and employs subjective language (e.g., “significant”) to describe

the magnitude of the decline, the NBER's explication appropriately designates the characteristics and tenets of a recession, thus providing a practical operational definition for this study.

Can Recessions be Forecasted?

While establishing a definition of a recession has been widely discussed in the literature, there is an even greater debate in the literature regarding the predictability of recessions. As with the definition of a recession, the literature is deeply divided on this subject. Recessions impose high costs on society. Adequate warning of an imminent recession may instigate policy maneuvers and other actions that may avert its onset or mitigate its impact (Filardi, 1999). Consequently, to limit exposure, forecasting business cycle turning points has become a critical imperative for policy makers and business planners (Dueker, 2002). Previous studies confirm that accurate recession forecasting remains elusive (Makridakis, 1981; Filardo, 1999; Del Negro, 2001).

To evaluate the extent to which economists and other forecasters have been successful in predicting the timing of recessions, Makridakis (1981) studied the chronology of the six U.S. recessions that occurred between 1960 and 1980. His dataset included the recessions of 1960/61, 1963, 1966/67, 1969/70, 1974/75, and 1979/80. Makridakis (1981) concluded that forecasters largely failed in their efforts to make meaningful predictions. Apart from predicting recessions that never materialized, the study found that forecasters found it particularly challenging to predict specific details regarding the timing of an oncoming recession.

Filardo (1999) conducted a study that measured the forecasting performance of five different recession-predicting models in terms of timeliness and accuracy. He found that, "some of the models missed spotting past recessions, some sent more false signals than others, some were more accurate at certain forecast horizons, and some were more robust to real time data

than others” (p. 48). Filardo concluded that no one model excelled as a recession prediction tool. Various other commentators, using decades of data, have contributed to this discussion (Dotsey, 1998; Chauvet & Potter, 2002; Giacomini and Rossi, 2009). Montier (2009) pointedly summarizes the prevailing consensus: "Frankly the three blind mice have more credibility than any macroforecaster at seeing what is coming” (p. 11).

Evaluation of Methods used to Forecast Recessions

The preceding studies and literary commentary converge on a common area of concern facing recession forecasting: the inability of forecasters to *consistently* provide correct, adequate, and timely information to policymakers, the business community and individuals (Pelaez, 2006). This failure to consistently make credible forecasts is attributable to many factors. Two agents that potentially expose the forecasting process to inaccurate outcomes are *data* utilized in forecasting models, and *methods employed* to make forecasts. To validate this assertion, an evaluation of the data and methods presently used by economists to make their predictions is necessary.

Data and data sources used in current forecasting models. Indicators and metrics that inform the forecasting models employed in business cycle forecasting originate either from U.S. Federal government agencies or private institutions. A considerable amount of economic data are thus available for analysis at any given point.

The U.S. government releases economic data through agencies such as the Bureau of Economic Analysis and the Federal Reserve Board. Among the most important private institutions is The Conference Board, a non-profit organization which gathers and uses various types of economic data to provide informed conclusions about the current and future economic environment and turning points in the economic cycle. Employing a process known as the

cyclical indicator approach, the Conference Board periodically releases a set of business cycle indicators, the most prominent being the index of leading economic indicators, or LEI index (Rogers, 1998).

The Council of Economic Advisors (CEA), a part of the Executive Office of the President of the United States, prepares a monthly economic report for the Joint Economic Committee. This report is a compilation of economic information on prices, wages, production, business activity, purchasing power, credit, money and Federal finance. Typical information furnished in this report includes GDP, unemployment rates, industrial production and capacity utilization, consumer prices and interest rates (Council of Economic Advisors, 2010).

The Economics and Statistics Administration of the U.S. Department of Commerce provides electronic access to the daily releases of key economic indicators from the Bureau of Economic Analysis and the U.S. Census Bureau. Included in this daily update are GDP, manufacturing and trade information, new residential construction and sales, personal income and outlays, and U.S. international transactions, among other indicators (Economics and Statistics Administration, 2010).

Among the most important economic datasets are the economic and financial indicators which are considered by The Federal Reserve in their determination of the nation's monetary policy (Federal Reserve Bank of New York, 2010):

- Real Gross Domestic Product (GDP)
- Consumer Price Index (CPI)
- Nonfarm Payroll Employment
- Housing Starts
- Industrial Production/Capacity Utilization

- Retail Sales
- Business Sales and Inventories
- Advance Durable Goods Shipments, New Orders and Unfilled Orders
- Yield on 10-year Treasury Bond
- S&P 500 Stock Index
- M2 Money supply

The information released by the U.S. Federal government is the most authoritative dataset for economic analyses or forecasting exercises.

Predictive Models.

The Conference Board's cyclical indicator approach. The composite economic indexes are the principal elements in an analytic system designed by The Conference Board to predict business cycles and other economic activity. Three composite economic indexes are employed: leading, coincident, and lagging economic indexes. The leading index is derived from the individual leading indicators, the coincident index is derived from the individual coincident indicators, and the lagging index is derived from the individual lagged indicators. The individual indicators are averaged to provide the composite indexes (see Table 1). Leading indicators are indicators that precede the change in the business cycle. For example, because stock market returns normally trend south before the economy goes into decline, they are regarded as leading indicators, i.e., they lead the economy. A coincident indicator moves in tandem with the economy. A lagging indicator changes direction well after the economy has. For example, the unemployment rate would normally increase after the economy has changed direction, and is thus regarded as a lagged indicator (Levanon, 2009).

These composite indexes serve the purpose of revealing common turning point patterns in economic data. The analytic system is designed to smooth out some of the volatility of individual components that feed into the respective economic indexes (The Conference Board, 2010). Table 1 identifies the individual indicators used to compute the composite economic indexes.

Table 1

U.S. Composite Economic Indexes

Leading	Coincident	Lagging
1. Average weekly hours, manufacturing	Employees on nonagricultural payrolls	Average duration of unemployment
2. Average weekly initial claims for unemployment insurance	Personal income less transfer payments	Inventories to sales ratio, manufacturing and trade
3. Manufacturers' new orders, consumer goods and materials	Industrial production	Labor cost per unit of output, manufacturing
4. Index of supplier deliveries – vendor performance	Manufacturing and trade sales	Average prime rate
5. Manufacturers' new orders, nondefense capital goods		Commercial and industrial loans
6. Building permits, new private housing units		Consumer installment credit to personal income ratio
7. Stock prices, 500 common stocks		Consumer price index for services
8. Money supply, M2		
9. Interest rate spread, 10-year Treasury bonds less federal funds		
10. Index of consumer expectations		

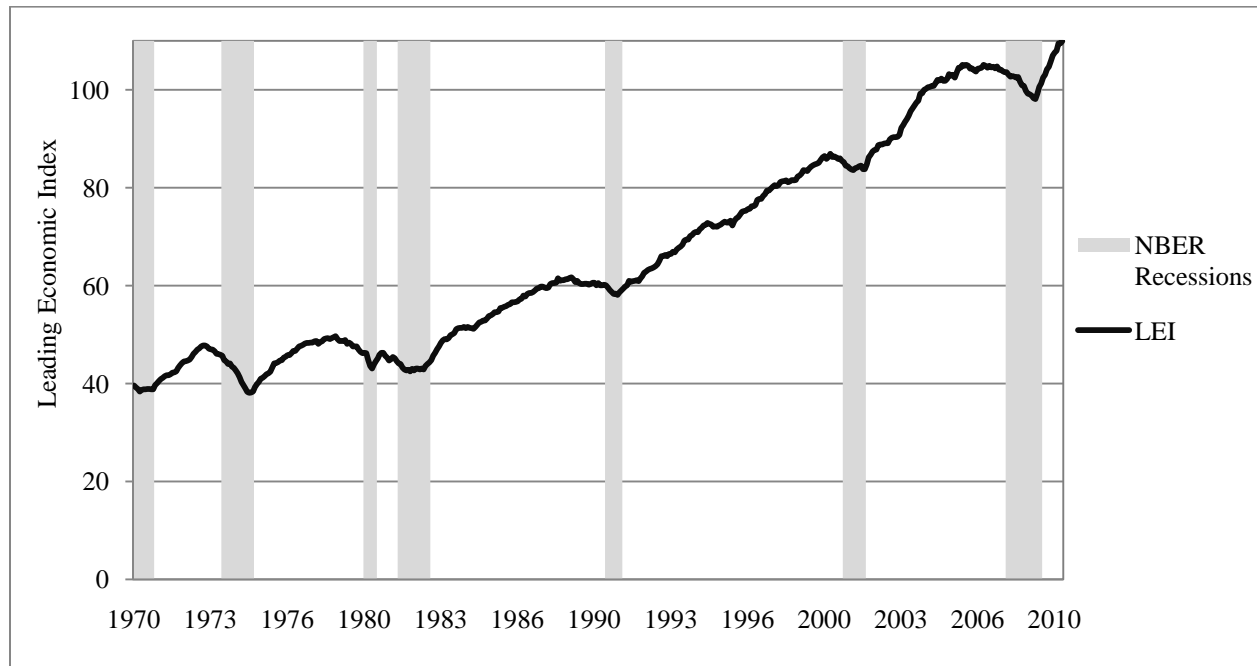
Note. Adapted from The Conference Board. (2010). *Global business cycle indicators*. Retrieved from <http://www.conference-board.org/data/bci.cfm>. Copyright 2010 by The Conference Board.

The composite economic indexes are analyzed by policymakers, economists and other stakeholders to assess the health of the economy and forecast the emerging stages of the business cycle. The leading economic indicators are the most important group of variables used by business economists to gauge whether a recession is approaching,. According to Del Negro (2001), the LEI has an advantage over more complex econometric models because the index is easily understood and interpreted, and is the oldest way to forecast business cycles.

Predictive power of the LEI. One of the critical tests of reliability of an economic forecasting system such as the LEI is its ability to make accurate forecasts over time. Various empirical studies have been conducted that have investigated the forecasting effectiveness of the LEI. Zarnowitz (1993) described the long-established record of leading indicators in predicting business cycle turning points as encouraging but commented that the main practical problem for this approach lies in false signals. To test the accuracy of the LEI in predicting future recessions, Zarnowitz and Moore (1982) conducted an empirical study of seven consecutive recessions, and found that the LEI successfully predicted each recession, without any false signals. Estrella and Mishkin (1996), in a study of the economy from 1971-1995, evaluated four different predictor variables. They found that even though all the variables demonstrated some forecastability one quarter ahead, the LEI produced the best forecasts over this horizon. Filardo (2004) evaluated four different predictive models in terms of their utility in predicting the 2001 contraction. He came to the conclusion the LEI was one of the most useful models among them. Keen (as cited in Lahiri & Moore, 1991) examined eleven consecutive recessions that occurred before 1983. He found that at least two months of negative growth occurred before each of these recessions, with an average lead time of 2.8 months. False signals of a recession were observed on four occasions.

Diebold and Rudebosch (1999) reviewed many of these studies and concluded that the LEI was ineffective and unreliable in terms of its ability to forecast cyclical turning points, and thus incapable of serving as a predictor of a recession. Silver (1991) observed that while the LEI may be a valuable tool in forecasting business cycle turning points, many of the individual indicators were not useful for predicting recessions. Del Negro (2001) corroborated Silver's conclusions and questioned the ability of the LEI to predict a forthcoming recession. He argued that the list of leading indicators were selected on the basis of their ability to predict, with hindsight, recessions that have already occurred. This hindsight does not exist when a future recession is predicted. To support his skepticism, he noted that the Leading Economic Indicators list is periodically revised because each new recession reveals that some indicators in the series were not good predictors. The only indicators from the original LEI series still in use are average weekly hours for manufacturing and the S&P 500 Index, with all other indicators from the list having been discarded. Burtini (2008) contends that when the LEI index was tested against the recessions of the past half century, it experimentally predicted every recession successfully. However, it also predicted nearly double the number of economic withdrawals that actually occurred. Figure 4 below maps the performance of the LEI index against NBER-defined recessions for a thirty-year period starting in 1970 and ending in 2000 (note that recessionary periods are indicated in grey on the chart).

Figure 5. LEI mapped against NBER recessions



The chart shows that the LEI index successfully predicted the 1973 recession. For the 1980 recession, however, the LEI index first decreases, then starts increasing at the start of the recession, which would have sent an inconclusive message to stakeholders. Further, there is no clear advance warning prior to 1981 and 1990 that a downturn in the economy is imminent, and an obviously erroneous signal of a recession is furnished for 1988.

In summary, the preponderance of evidence suggests that while leading indicators may be useful in predicting recessions, some gaps do manifest with regard to its consistency, and much ambiguity still appears to exist when it comes to the accuracy and timing of the predictions.

Econometric models. Econometrics involves the use of statistical methods to explain economic fluctuations. This is achieved through examining correlations in economic data. A wide variety of macroeconomic data are analyzed and historical relationships are inferred. These historical relationships are then extrapolated to make future economic forecasts (Hayashi, 2001). Among the predictive models evaluated by Filardo (2004) to assess how well they predicted the

2001 recession were Neftçi's Sequential Probability Model, the Probit Model and Stock and Watson's Experimental Recession Indexes. While Neftçi's Sequential Probability Model proved to be useful, the other models failed to deliver the same level of accuracy consistently. Estrella and Mishkin (1998) argued the merits of the probit model, which employs an array of economic variables including macroeconomic indicators, interest rates, and stock prices to predict business cycles. They found that stock prices and certain leading macroeconomic indicators were effective predictor variables.

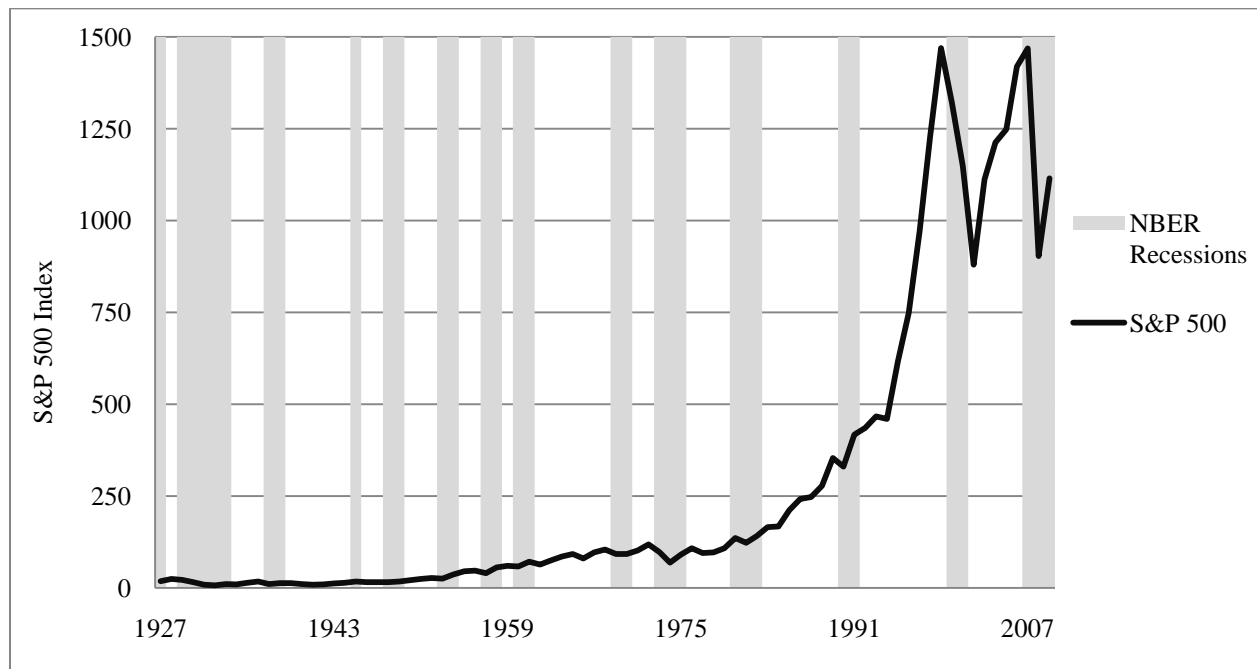
The data used in econometric models are extracted from the official economic data released by the government as well as other economic research institutions. As a result, it employs the typical datasets identified in the other models discussed above, i.e., GDP, consumer price index, unemployment rate, etc. Because the data modeled in econometrics is largely similar to that used in developing the Conference Board's composite economic indexes (see Table 1), similar strengths and deficiencies manifest in this method.

The stock market as predictor. A stock market decline of at least 10% of the overall value of the market is considered by many to be one of the most reliable predictors of a recession. Thus, the stock market has historically been seen as the most sensitive indicator of the business cycle and the most powerful variable in the index of leading economic indicators (Siegel, 1991, du Plessis, 2010). This sentiment, however, is not universally embraced. Even though its predictive power is well-regarded among forecasters, the stock market has earned the reputation of crying wolf on many occasions. This led to Samuelson's declaration "The stock market has predicted nine out of the last five recessions" (as cited in Barro, 2009, para. 6). Though somewhat tongue-in-cheek, there is no mistaking that this remark was a castigation of the stock market as a reliable predictor of economic recessions. A fall in share prices does not

always signal a downturn in the economy. A case in point is the 1987 stock market crash, which left the major economies of the world relatively unscathed (Barro, 1989).

Figure 5 highlights the performance of the stock market as a predictor of NBER recessions:

Figure 6. The S&P 500 Index mapped against NBER recessions



The chart highlights that, without exception, the S&P 500 Index declined in every NBER- identified recession. However, there are two notable inefficiencies when this process is used to predict recessions:

1. the lead time of the decline was not always of significant duration to warn of an impending recessionary period, and
2. some significant declines in the S&P 500 Index is observed in non-recessionary periods.

With regard to the lead time, for the recessions of 1957 and 1980, for example, the S&P 500 Index was actually trending upwards before the recessionary period. The decline in the index only occurred after the recession was in full swing. In a recent study, Hulbert (2008) examined

the historical performance of the stock market with regard to lead time. His study focused on 28 NBER-defined recessions since the 1870s. He evaluated the performance of the stock market using four periods leading up to when each recession began: three months, six months, one year, and two years. Table 2 summarizes his findings:

Table 2

Stock market predictive performance since 1870

Time Period	Number of times stock market declined before the recession began (28 recessions observed)
3 months before recession	Stock market declined 18 times
6 months before recession	Stock market declined 15 times
12 months before recession	Stock market declined 10 times
24 months before recession	Stock market declined 6 times

Note: Adapted from Hulbert, M. (2008). *Can the stock market predict the next recession?* Retrieved from <http://online.barrons.com/article/SB119980107558974769.html>. Copyright 2010 by Dow Jones & Company, Inc.

Disturbingly, this study found that even as close as three months before the beginning of a recession, stock market declines occurred in only 18 instances, suggesting a 64% success rate, which is relatively low given the proximity to the beginning of the recession. A year before the beginning of a recession, stock market declines occurred in approximately a third of the instances – a statistic that is both alarming and perplexing.

A second inefficiency can be found in the observation that, between 1960 and 1970, for example, there are two significant declines in the index. Neither decline, however, preceded a recession. Similar patterns surfaced in the following two decades. According to Siegel (1991), a total of eight false alarms were generated between 1950 and 1990. Hulbert (2008) commented,

“the only solace stock-market bulls can get from the stock market’s history prior to past recessions is that it is often a faulty predictor” (para.15).

Bagalore’s (2008) study of movements of the S&P 500 Index just prior to and during recessions from 1950 to 2001 concluded that the stock market remains an important leading indicator of potential contractions in the economy. However, it does boast a disconcerting post World War II record of only peaking an average 2.4 months before the business cycle, and generating a significant number of false alarms (Siegel, 1991). Mester (2007) asserted that “[the stock market] is so filled with false signals that it cannot be a reliable indicator by itself” (p. 2254).

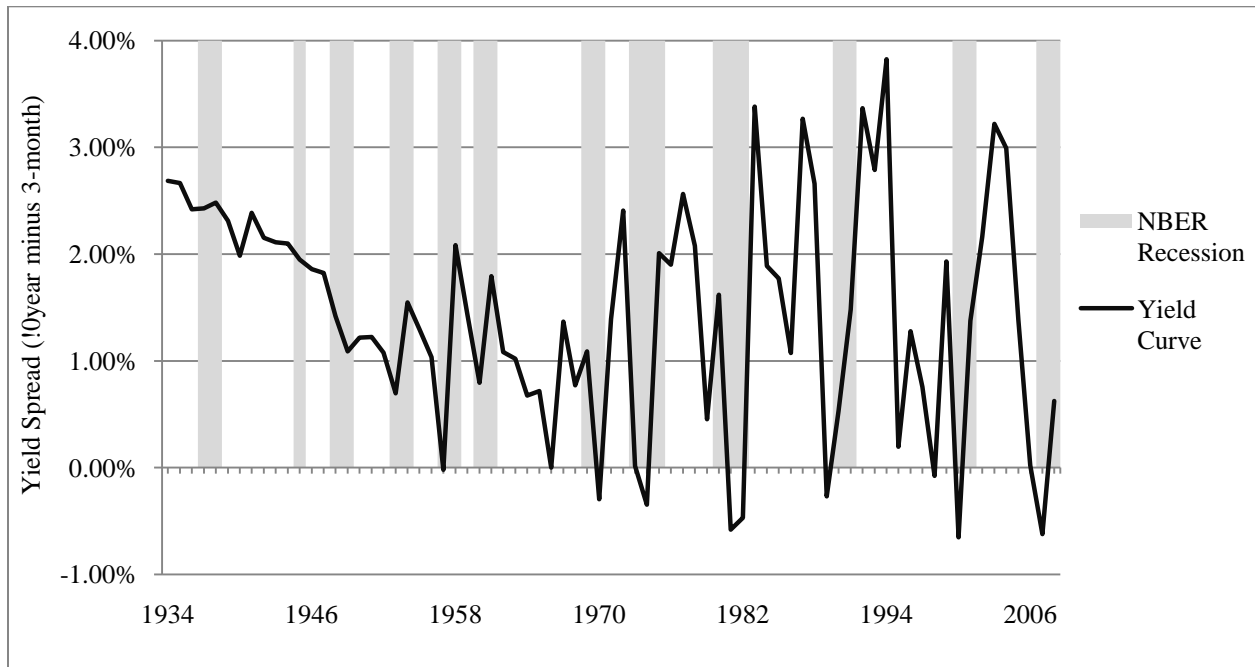
The yield curve as predictor. The U.S. Treasury issues various types of government debt (securities), which range from short-term to long-term. These securities are the debt financing instruments of the government (Fleming, 1997). Four types of securities are issued: Treasury bills, Treasury notes, Treasury bonds, and Treasury Inflation Protected Securities (TIPS). Treasury bills are redeemable in one year or less; treasury notes mature in one to ten years; treasury bonds mature between twenty years to thirty years; and TIPS are currently offered in five-year, ten-year and 30-year maturities (Amihud & Mendelson, 1991). These securities can be bought directly from the Treasury or from others who are selling off their purchased bonds. The yield to maturity, sometimes simply referred to as the yield, is a mathematical calculation that takes into account the interest received (coupon payments) for the bond, the price paid for the bond, and the original face amount of the bond (Caks, 1977). It is, in essence, a measure of the return on holding the bond, i.e., what interest the bond will generate based on the current price that the bond is selling for (Knoop, 2004).

Campbell (1995) defines the yield curve as “the relationship between short and long term interest rates” (p. 1). The yield curve is a graph that illustrates the relationship between yield and maturity among similar debt securities. The vertical axis represents increasing yields and the horizontal axis identifies the years to maturity. Because yields rise as maturity lengthens, short-term interest rates are normally lower than long-term interest rates. Therefore, the line slopes upward for a *normal* yield curve. When there is no difference between short and long-term yields, a characteristic *flat* yield curve results, often indicating market uncertainty (Hemmerdinger, 2008). It is, however, the *inverted* yield curve that is of most concern to forecasters, because it is seen as a harbinger of recession. When the curve slopes downward, it indicates that short-term rates have risen above long-term rates, and the spread is negative. This scenario signals the probability of a recession (Campbell, 1995).

The usefulness of the yield curve for forecasting recessions has been particularly well established. Since the 1980s, an extensive body of literature has developed in support of the yield curve as a reliable predictor of recessions (Estrella and Trubin, 2006). According to (Knoop, 2004) yield curves in the United States have been a very reliable indicator of recessions over the last 30 years. In their study of the economy from 1971-1995, Estrella and Mishkin (1995), evaluated four financial and macroeconomic variables that predicted the likelihood of a recession. They found that the yield curve significantly outperformed other financial and macroeconomic predictor variables in predicting recessions two to six quarters ahead. Various other studies examining the forecastability of the yield curve with regard to recessions have found that the yield curve is a good predictor of recessions (Hu, 1993; Wright, 2006; Hamilton & Kim, 2002, Kozicki, 1997). Estrella & Trubin (2006) found that the yield curve was very successful in predicting the recessions of recent decades. Between the periods 1968-2006, the

average spread between the short term and the long term debt securities turned negative before every recession in that period. Their study showed that the estimated probability of a recession exceeded 30 % in each case, and was as high as 98 % for the 1981-82 recession. Figure 6 highlights the movement of the yield curve relative to NBER recessions:

Figure 7. The yield spread (ten year rate minus three month rate) mapped against NBER recessions



In a study for the Federal Reserve Bank of Cleveland, Haubrich (2006) observed:

Despite the evidence linking the yield curve to economic growth, and even though yield-curve inversions precede the two most recent recessions, many have suggested that the yield curve no longer reliably predicts economic growth. Noting that the economy is continually evolving, particularly in the financial sector, they discount past successes. They point to recent ‘near-misses’ in 1995 and 1998, when a flat yield curve did not presage slow growth. And indeed, evidence since the early 1990s suggests that the relationship between the yield curve and growth has shifted, if not disappeared (p. 26).

Haubrich and Dombrosky (1996) found that that even though the yield curve was a good predictor over the entire 30-year sample period they studied, it had become much less accurate over the last decade. This was corroborated by Chauvet and Potter (2001), who found that while

the yield curve is a statistically significant predictor of future activity, its predictive power is not stable over time.

Gap analysis. Perceptible tension exists in the literature regarding the validity, range and scope of each of the models and methods used by forecasters to predict recessions. As highlighted above, for each of the different methods or tools currently employed, there are opposing arguments for and against its usefulness as a predictor.

Echoing the sentiments in the literature, Zarnowitz (1986) contends that:

Forecasters tend to rely heavily on the persistence of trends in spending, output, and the price level. To the extent that inertia prevails in the economy's movement, their predictions turn out to be roughly right, at least directionally, most of the time. But the inertia, although helpful in this sense, is only a part of the story, and such forecasts suffer from missing business cycle turns and underestimating recessions and recoveries with respect to both their real and nominal effects (p. 17).

While no clear consensus emerges as to which is the most accurate model, the yield curve has garnered a respectable degree of credibility as a forecasting tool, with various studies positioning it above other forecasting models in terms of its historical accuracy. However, the lack of unified consensus begs further inquiry. Much of the contention emerging from the literature ostensibly relates to the data variables employed by the respective models. For example, as highlighted above, the stock market approach looks at movement of stock prices. Thus, when critics comment on the inefficiency of the stock market approach, they are essentially providing a de facto criticism of the use of stock prices as predictor variables. This criticism can reasonably be extrapolated to the other models evaluated in this study. If data variables employed by current forecasting models are, indeed, at the nexus of the contention,

then a door is opened for the consideration of other data that may serve to enhance predictive forecasting. To this end, a value proposition exists for the inclusion of institutional artifacts (government and corporate) as potential input variables in predictive forecasting models.

In summary, this section of the literature review evaluated the strengths and weaknesses of current forecasting models used to predict recessions, the data that these models employ, and the sources that these data are extracted from. The preponderance of evidence suggests that the inverted yield curve is far better positioned than other models as a reliable predictor of recessions. Also highlighted in this section was the gap inherent in current forecasting techniques. To address this gap, institutional artifacts are selected as potential input variables in forecasting models because of the crucial information they embed. However, in order to legitimize institutional records as potential economic variables, theoretical support is important.

Overarching Theories: Macroeconomic Theories of Business Cycles and Forecasting

The Classical model. The classical paradigm, widely regarded as the first modern school of economic thought, began with Smith's (1776) *Wealth of Nations*, in which he set out the fundamental principles of classical economics. His ideas were subsequently advanced by the works of Ricardo (1810) and Mill (1909). The classical model focused on the dynamics of economic growth, and emphasized economic freedom and free competition (Blaug, 1987). The classical paradigm subscribes to the labor theory of value, which says that the value of a commodity is equal to the amount of labor required to produce it.

The aspect of the classical model that brings to bear on this study is the production function: $Y = F(L, K)$, where Y denotes real aggregate output, L denotes labor employed, and K denotes the total stock of capital. Real aggregate output is an important determinant of an economy's proclivity towards a recession, so the variables impacting it are carefully tracked.

Consequently, the factors influencing the quantity of labor and the quantity of capital are an important consideration in predictive forecasts.

Factors that influence the quantity of labor. Apart from immigration and population growth, government fiscal policy is an important influence on labor supply and labor demand. Imposition of increased personal income taxes, for example, may reduce individuals' incentives to participate in the workforce, thereby reducing labor supply, while increased taxes on organizations' payrolls may reduce the demand for labor (Knoop, 2004)

Factors that influence the quantity of capital. When firms are incentivized to increase capital spending, aggregate output increases. The corollary argument also holds true. Government tax policy and other federal regulations may incentivize or de-incentivize firms from making capital investments, thereby impacting aggregate output. Similarly, government income tax policies may shape how much households and individuals save. Tax policies that promote consumption and spending may reduce the quantity of funds available for investment, thereby reducing quantity of capital (Knoop, 2004).

In summary, Knoop (2004) suggests that classical economists focus on one primary culprit when it comes to explaining and forecasting economic contractions: government policy. This provides forceful evidence of the relevance and usefulness of tracking institutional activity (in terms of public policy) as it pertains to forecasting recessions.

The Keynesian model. Keynesian theory, perhaps appropriately, emerged out of trying to explain and devise a cure for the Great Depression. Keynes's (1936) explanation of economic contractions was very simplistic: A normal economy is characterized by a high level of employment, and earnings are spent on goods and services. A circular flow of money gets established in the economy as one person's spending becomes part of another person's earnings,

and vice versa. However, in the event of something happening to shake consumer confidence in the economy, concerned consumers may try to mitigate the ensuing economic hardship by saving their money. But because one person's spending is part of another's earnings, the decision to hold onto money places the latter in a precarious financial position. Similarly, the latter person, responding to their own financial predicament, will start holding onto their money too, thereby reducing the earnings of someone else. Thus, an oppressive cycle is at play: people save money in difficult times, but times become more difficult when people save money. To break this unwelcome cycle, Keynes advanced that the central bank ought to expand the money supply (M2). Essentially, by putting more money in consumers' hands, consumer confidence would return, spending would resume, and the circular flow of money would be reinstated (Kangas, 2010; Fazzari and Minsky, 1984).

Based on the premise that falling aggregate demand is the source of recessions (Blinder, 1988), Keynes felt that government intervention was necessary to stabilize aggregate demand in a weakening economy. He argued that fiscal and monetary expansion were an appropriate policy response to downturns and recessions (Hodgson, 2002). If the government institutes suitable public policies and increase the money supply (M2), more money will find its way into the hands of consumers, and aggregate demand will increase. He maintained that higher aggregate demand would, among other things, increase spending (increased consumer confidence), increase the price level, reduce unemployment, and potentially increase stock market returns through restored investor confidence (Knoop, 2004).

This theory has substantial relevance for this study. With its emphasis on the enactment of appropriate public policy by the government, the importance of institutional activity is once again reinforced. Additionally, the variables considered by Keynes, for example,

unemployment, stock prices, money supply (M2), interest rate, and index of consumer expectations are all component variables of the Leading Economic Index (LEI), which is a critical forecasting variable.

Theory of Rational Expectations. The Rational Expectations paradigm has become a widely accepted component of macroeconomics and is attributed to Muth (1961). He postulated that “expectations of firms (or, more generally, the subjective probability distribution of outcomes) tend to be distributed, for the same information set, about the prediction of the theory (or the ‘objective’ probability distributions of outcomes)” (1961, p. 316). Given its somewhat awkward posturing, other proponents of this theory endeavored to clarify the definition. Sargent and Wallace (1975) offered that “the public’s subjective expectation equals the objective mathematical expectation conditioned on data available when the expectation was formed” (As cited in Swamy et al., 1981, p. 127) while Lucas (1976) adduced that “a true (objective) probability distribution is equal to the subjective distribution on which decisions are based” (As cited in Swamy et al., 1981, p. 27). In plain language, this theory proposes that “individuals form their expectations by making an optimal forecast of the future using all currently available information” (Knoop, 2004, p. 80). This theory is rather unconventional because it embraces both subjective and objective probabilities. It also violates the axiomatic basis of much of modern econometrics, which employs statistical models (Swamy, et al., 1981).

Despite its unconventional approach, the theory’s relevance to this study is found in the premise that rational expectations imply that the public is contemplating all possible variables that affect the future of their economy. In other words, they focus not only on the statistical economic data that form the basis of economic forecasting, but also on other contemporaneous impacts, so that they have a more well-informed view of the business cycle. Of particular

saliency is the fact that this theory asserts that only unexpected changes in policy can actuate business cycles, implying that changes in government policy are responsible for driving swings in the business cycle (Knoop, 2004). This assertion supports the rationale that institutional activity is a critical influence on business cycle troughs and economic recessions. Additionally, it promotes the notion that economic forecasting analysis is multidimensional, urging forecasters to extend the boundaries of the current datasets.

In summary, all three theoretical models identified above posit institutional activity as being inextricably linked with business cycles, and reinforce its importance as an arbiter of economic activity. The assertion in the rational expectations model that changes in policy can actuate business cycles suggests that by observing and examining government policy changes, turning points in the business cycle could potentially be predicted. In explicitly highlighting government institutional activity as an important determinant of economic activity, these theories also tacitly highlight the economic importance of another component of institutional activity: corporations. Government monetary and fiscal policy affects the aggregate level of output by changing the incentives that firms face. A fiscal policy change, like a decrease in taxes, for example, provides households more disposable income with which they can buy more products, thereby stimulating aggregate demand. This increase in aggregate demand stimulates firms to increase production, and consequently, their revenues. Similarly, a monetary policy change, like a decrease in interest rates, for example, encourages firms to borrow money to make capital investments, increase output, and presumably increase revenue.

The theoretical models collectively provide strong support for the inclusion of government and corporate institutional records as input variables in recession forecasting

models. While the theoretical models support the inclusion of institutional records, they do not specify which institutional records ought to be included.

Contextualization of Variables

Macroeconomic variables. Earlier in this chapter an assortment of economic variables were introduced that are currently employed in forecasting economic activity. Because the range of data is comprehensive, it is necessary to refine the list so that it only incorporates those variables that are deemed pertinent to this study. Previous studies were examined to facilitate the filtering process and provide justification for the final list of macroeconomic variables analyzed in this project.

Estrella and Mishkin (1998) found that leading macroeconomic indicators were effective predictor variables of economic cycles. To ascertain what constitutes a leading macroeconomic indicator, the Leading Economic Index (LEI) was probed based on the use of leading macroeconomic indicators to compute the LEI. Consequently, the outcome of any critical study of the LEI necessarily reflects on leading macroeconomic indicators. Of importance to this project are studies supporting the effectiveness of the LEI as a good predictor of business cycles because they tacitly reinforce the efficacy of leading macroeconomic indicators as good predictor variables. As evidenced in an earlier section of this literature review, these studies abound in the literature, e.g. Del Negro's (2001) finding that the LEI had an advantage over more complex econometric models in terms of accurately forecasting business cycles; Zarnowitz and Moore's (1982) empirical study of seven consecutive recessions which found that the LEI successfully predicted every one of these recessions, without any false signals; Keen's (1983) study that examined eleven consecutive recessions and concluded that the LEI was one of the most useful predictive models; and finally, Filardo's (2004) study that corroborated the findings of the

preceding studies. While the LEI provided the predominant influence for the selection of the macroeconomic variables, to extend the reach of this study and to ensure completeness, the other indicators that constitute the U.S. Composite Economic Indexes were also considered, namely, coincident and lagging indicators (see Table 1). Thus, the final list of macroeconomic variables analyzed in this study incorporates leading, coincident, and lagging indicators.

The yield curve. The identification of a dependent variable is necessary to facilitate the development of the predictive model. To this end, a quantitative measure of a recession is required. Given the vast array of predictive models that have been developed and employed in forecasting recessions (as highlighted in the preceding sections of this literature review), there is no established consensus on what constitutes a definitive measure. The preponderance of evidence in the literature suggests that the yield curve may be one of the most stable, robust predictors of recessions. This assertion has been corroborated by both U.S. institutional authorities (e.g., The Federal Deposit Insurance Corporation, 2006) and industry experts and scholars, as noted earlier (e.g. Chen, 2009; Hu, 1993; Wright, 2006; Hamilton & Kim, 2002; Kozicki, 1997; Estrella & Mishkin, 1996; and Estrella & Trubin, 2006).

According to the Federal Deposit Insurance Corporation (2006), there are many different yield curves and many ways of measuring the difference, or spread, in short and long-term interest rates along these curves. Three common measures are employed: (1) the spread between the federal funds rate, which is set by the Federal Reserve and used in pricing overnight interbank loans, and the ten-year Treasury note yield, which is linked to the pricing of traditional fixed-rate mortgages, (2) the difference between three-month and ten-year Treasury yields, and (3) the difference between two-year and ten-year Treasury yields. Market analysts have traditionally favored the use of the difference between two-year and ten-year Treasury yields,

while academic researchers have been partial towards the spread between the federal funds rate and the ten-year Treasury note yield.

Research shows that calculating spreads using short-term rates, such as the three-month Treasury yield, is a more useful indicator of future economic activity than using a two-year Treasury yield as a short-term rate. In a study conducted by Estrella and Mishkin (1996), it was found that the “three-month Treasury rate, when used in conjunction with the ten-year Treasury rate, provides a reasonable combination of accuracy and robustness in predicting U.S. recessions over long periods” (p. 3). An important finding in their study was that when the three-month Treasury rate was used in conjunction with the ten-year Treasury rate to generate the yield curve, the resulting yield curve significantly outperformed other financial and macroeconomic indicators in predicting recessions two to six quarters ahead. In addition to its accuracy and robustness, the study asserted that this specific yield curve’s simplicity of use, the ready availability of historical data, and the consistency in the computation of rates over time further enhanced its value as an effective forecasting tool.

With the identification and description of the nature of all the relevant data that is being analyzed in this study complete, the next section is concerned with identifying appropriate techniques for collecting, processing and analyzing this data.

Institutional Artifacts.

Presidential rhetoric.

The rhetorical context. According to Tulis (1996), all presidents exercise their office through the rhetorical medium, written and spoken, and routinely delivered rhetoric to the public is an essential feature of governance. He goes on to suggest that presidential rhetoric traditionally highlights priorities and emphasizes the principles upon which the president wants policy

constructed. These priorities and principles are largely driven by the rhetorical context confronting the president at a particular point in time. Medhurst (1996) identifies a rhetorical context as comprising of a unique arrangement of forces that prevails at any given moment in time and that impacts the speaker's selection of and presentation of topics. This arrangement may include historical, sociological, psychological, personal, strategic, and economic forces. If, in fact, the rhetorical context does set the presidential agenda, it elevates the presidency to more than just primarily an office of constitutional responsibility.

An example of the expanded role of the presidency emerged after World War II, when Congress passed the Employment Act of 1946. According to Wood (2007), this legislation "formally institutionalized an activist role for the president, charging government with promoting 'maximum employment, production and purchasing power,'" (p. 6) and from this point forward presidents were required to present an annual Economic report to Congress, which addressed the current and future state of the economy. This, and the subsequent evolutions of institutions over the years, contends Wood further, imposed various accountabilities on the presidency, which has resulted in presidents being constantly engaged in economic affairs. The burden is exacerbated by the fact that the public holds the president accountable for the economy, and alter their opinions about the president based on the state of the economy. To this end, presidents are kept apprised of the state of the economy through regular briefings, and are active participants in the formulation and implementation of economic strategy. The economy is thus an indelible part of the president's rhetoric (2007).

Further emphasizing the importance of economic forces as a critical component of the rhetorical context, various studies corroborate the importance of good presidential stewardship of the economy and how it impacts reelection prospects. Bartels (1997) found that "Economic

conditions are the single most important influence on an incumbent president's reelection prospects" (p. 5). Erikson (1989) argued that the state of the economy is a major determinant of presidential election outcomes. Finally, Nadeau and Lewis-Beck (2001) found that U.S. presidential elections are regularly impacted by economic conditions in the country.

Wood (2007) poses a poignant question in a recent empirical study of presidential rhetoric: How do economic conditions affect the intensity and tone of presidential remarks about the economy? He defines intensity as a measure of the quantity of attention directed by presidents towards matters of economic importance, and "tone" as a measure of the relative optimism exuded by presidents in their remarks about the economy. To answer this question, he examined the *Public Papers of the Presidents* from 1945 through to 2005. Using content analysis methods, he analyzed each unique sentence within presidential speeches as well as rhetoric from other public events. He employed four keywords to code the individual sentences spoken by the president: (1) economy, (2) unemployment, (3) inflation, and (4) deficit. Among the findings of his study was that presidential rhetoric responds systematically to what the public perceives as being important issues. As the public's sensitivity to unemployment, inflation, the deficit, and other general economic issues increased, it was accompanied by a parallel increase in the intensity of presidential rhetoric on those issues.

Does presidential rhetoric matter? The field of presidency studies is dominated by a research paradigm that emphasizes presidential rhetoric, e.g., Tetlock, 1981; Cohen, 1995; Druckman and Holmes, 2004; Windt, 1984; and Zarefsky, 2004. The fundamental premise scaffolding a vast majority of studies is that rhetoric exerts a powerful influence on the public. This assertion is confirmed by Edwards (1996), who examined several prominent studies relating to the influence of rhetoric. He concluded that "authors explicitly or implicitly operate on the

premise that the president can employ rhetoric to lead the public” (p. 209). Edwards (1996) goes on to argue that this premise may be flawed because, “the authors often fail to provide evidence to support either their broad premise or its application in specific instances” (p. 209). A large body of literature, however, refutes Edwards’ skepticism and provides evidence of the power of presidential rhetoric in specific instances. Stuckey’s (2006) examination of President Roosevelt’s rhetoric over the “proper” interpretation of the Brownsville Raid, for example, highlighted the power of presidential rhetoric “as it pertained to ideologically based definitions of national identity and the role of minorities within that identity” (p. 287). She goes on to contend that the presidential rhetoric both justified his dismissal of the soldiers and increased the definitional power of his institution. In another instance of the power of presidential rhetoric, President Carter, in 1979, concluding that the nation was experiencing a crisis of spirit or malaise, engaged in a rhetorical campaign to revive the nation and restore national morale. The presidential rhetoric is commonly thought to have marked a turning point in the nation during the Carter presidency (Ceaser, et al., 1981).

Generative versus reactive rhetoric. In both instances identified above, presidential rhetoric was used to encourage the public to embrace a specific presidential agenda. Notably, the engagement of rhetoric in both cases was largely a reactive measure – an event manifested, and presidential rhetoric was employed to “move the public, change opinions, mobilize citizens into action, and place new issues on the public’s agenda” (Edwards, 1996, p. 210). From an economic policy-oriented perspective, however, presidential rhetoric often carries the burden of having to be *generative* rather than *reactive*. Generative rhetoric prepares the public in advance for an event that may potentially occur in the future, while reactive rhetoric emerges in response to an event that is occurring or has already occurred. Thus generative rhetoric has the power to

position the public more optimally against future adversity by increasing their readiness. Reactive rhetoric, on the other hand, is less postured to do so.

An important instrument of presidential rhetoric is the presidential executive order. As an instrument of executive power, presidents have employed executive orders to shape and influence the institutional and political context over which they preside.

Presidential executive orders. The number of statements on a topic in a given presidential address is generally construed as an indicator of presidential priorities. For example, in State of the Union addresses, presidents generally identify a number of agenda items for congressional consideration. Analysts view this as the president's delineation of the government's current agenda (Baumgartner et al, 2009).

The volume of executive orders issued on a given topic in a given year is another indicator of presidential priorities (Baumgartner et al, 2009). Executive Orders are legal instruments of executive power that allow the President to make major decisions without the consent of Congress. Mayer (2001) argues that, "By themselves and as a broader indicator of executive authority, executive orders constitute a potent source of presidential power," (p. 10) and, within legislative and constitutional parameters, presidents have consistently used executive orders to shape the institutional and political context over which they preside.

Mayer (2001) goes on to comment that, despite the potential importance of executive orders, the literature within the various disciplines has paid meager attention to them. According to Mayer, "most of the studies that do exist have minimized the significance of executive orders, viewing them as useful only for routine administrative tasks" (p. 10). In rebuttal he declares that, even if they are routine administrative tasks, purely administrative decisions can still have far-reaching ramifications on the political, institutional and economic landscape. Research, however,

indicates that executive orders have evolved from a primarily administrative tool to a policy-making tool (Baumgartner et al, 2009).

Congressional committee hearings. Congressional hearings can be used as a general barometer of the intensity of interest or activity in a particular area (Baumgartner et al, 2009). The objective of these hearings is “to obtain information and opinions on proposed legislation, conduct an investigation, or evaluate/oversee the activities of a government department or the implementation of a Federal law. In addition, hearings may also be purely exploratory in nature, providing testimony and data about topics of current interest” (GPOAccess, 2010, para. 1). Since hearings are an indicator of congressional involvement in a policy area, it is expected that hearings relating to monetary and fiscal policy, as well as other economic issues, would have an important impact on the economic landscape, and demonstrate the level of government activity in the issue area (Baumgartner et al, 2009).

A large number of political science research studies have found that public bureaucracies respond to catalysts that manifest in the policy environment. These catalysts may originate from higher up in the institutional hierarchy or from the public (Wood & Waterman, 1993). Weingast and Moran (1983) found that politicians, feeling threatened by their constituents, act in a manner that mitigates such threat. Consequently, policy decisions tend to be partial towards constituents’ leanings (Banks & Weingast, 1992). This would be an example of a public catalyst, or a bottom-up stimulus.

Moe (1982) postulated that independent regulatory commissions were not really independent of presidential direction and control. Chubb (1985) corroborated this assertion in a study that found that “political effects can be disaggregated into ideological and constituency-oriented demands made by Congress and the White House” (p. 994). This would be an example

of top-down stimuli, i.e. catalysts from higher up in the institutional hierarchy. Ultimately, what the literature conveys is that whether the stimuli originate top-down or bottom-up, the agenda for congressional committee discourse is set by stimuli from the policy environment.

By virtue of the office, it is reasonable to assume that the presidential agenda will be focused on high-priority items affecting the nation. An acute focus on any particular issue may signal a looming or extant problem in the relevant social, political, or economic environment. Thus, if the presidential policy agenda has a distinct economic focus, for example, this might potentially be indicative of prevailing or imminent problems with economic fundamentals. To this end, the likelihood of congressional committee agendas being concentrated around economic issues is greatly increased. Similarly, if economic issues are of pre-eminent concern to constituents, the likelihood of congressional committee discourse being concentrated around such issues is greatly enhanced.

As is the case with presidential rhetoric, economic policy-oriented research is concerned with whether the congressional committee rhetoric is generative or reactive. To this end, ascertaining whether the corollary argument also holds true - if congressional committee hearings are increasingly oriented towards a particular subject, is this indicative of a prevailing or looming threat in the environment relating to that subject – will yield valuable information for economic research.

Fortune 500 company data. Liou and Smith (2006) posited that one of the driving forces of any economy is the interaction of the individual companies within it. As a matter of course, then, the economy is acutely sensitive to changes in the relative financial health of these individual companies. A study conducted by Anderson and Cavanagh (2000) found that of the world's 100 largest economic entities, 51 were publicly traded corporations and 49 were

countries. It is no wonder that scholars assert that firms play the role of intermediary between society and state and are involved in power relationships in the domestic nation-state that shape the market (Sally, 1995). Conason (2010) posits that it is the culture of American government, from the executive branch to Congress, and even the judiciary, to demonstrate an ideological deference to corporate power, in the name of free markets and efficiency. When the balance of economic power is tilted so heavily in favor of corporations, their impact on the business cycle cannot be overstated.

A review of the U.S. Composite Economic Indexes affirms this notion. All three composite economic indexes (leading, coincident and lagging) employ data that are derived from corporate economic activity (e.g. manufacturers' new orders, consumer goods and materials, index of supplier deliveries – vendor performance, industrial production, and manufacturing and trade sales). Of course, the data used to compute the economic indexes are aggregated from the industry as whole. However, within the industry, there are always high-profile corporations whose economic performance can significantly influence the aggregate numbers and, thus, the economy as a whole. These high-profile companies are usually the traditional mainstays of the U.S. Fortune 500 list. Companies on the U.S. Fortune 500 list are the building blocks of the U.S. economy and are therefore an appropriate benchmark for evaluating corporate profitability (Deile, 2003). Hasan (2008), corroborating this statement, adds that the economic strength of cities is said to be quantified by the presence of Fortune 500 companies. This testament to their prominence as pillars of the U.S. economy predicates their usefulness as barometers of economic activity.

To this end, data generated by U.S. Fortune 500 companies may offer predictive insights into the path of the economy. Careful analysis of these companies' productive efficiency and

profitability over a particular period may yield predictor variables that may strengthen forecasting models. Lewellen (2004) and Park (2010) charge that financial ratios such as dividend yield, book-to-market ratio, and earnings-price ratio have solid predictive power, which helps to provide insight into whether a company's financial health is improving or deteriorating over time.

Industry analysts frequently employ financial ratios as a tool for analysis and planning. Among the informational advantages provided by financial ratios is their considerable predictive ability. For example, studies confirm that financial ratios are frequently used for the probabilistic prediction of bankruptcy (Ohlson, 1980; Beaver, 1966; Altman, 1968). Thus, given the goals of this study, the inclusion of financial ratios is a plausible extension to the list of data variables selected for analysis.

Data Analysis

Data mining and predictive analytics. The process of selecting, exploring and modeling large amounts of seemingly disparate data to uncover new relationships and patterns is called data mining (Seifert, 2004). The next step in the process is applying these patterns to make future predictions. When quantitative techniques are employed to apply patterns and relationships that exist in mined data, the process is called predictive analytics. According to the Technology

Evaluation Center:

Predictive analytics is used to determine the probable future outcome of an event, or the likelihood of a situation occurring. It is the branch of data mining concerned with the prediction of future probabilities and trends. Predictive analytics is used to analyze large amounts of data with different variables....Multiple predictors can be combined into a predictive model, which, when subjected to analysis, can be used to forecast future probabilities with an acceptable level of reliability. In predictive modeling, data is collected, a statistical model is formulated, predictions are made, and the model is validated (or revised) as additional data becomes available (2009, para. 3).

Predictive analytics is thus useful for understanding historical trends and predicting future outcomes. Ebecken and Brebbia (2000) conducted a parallel study that used data mining techniques and predictive analytics for microeconomic and macroeconomic modeling. Their study looked at correlations between macroeconomic indicators and corporate output variables such as gross profit and quality indicators. Safer (2003) used data mining and predictive analytic techniques to devise a model for the prediction of abnormal stock market returns. Sung, Chang and Lee (1999) created a model for the prediction of corporate bankruptcies. Tjung, et al (2010) used data mining techniques to forecast daily changes in seven financial stocks' prices. Their model incorporated eight indicators that included macroeconomic leading indicators (market indexes), government institutional indicators (presidential election date and party), and market sentiment, corporate data, and business cycles to predict changes in daily financial stock prices.

The common thread of these studies is their success at effectively leveraging data mining processes and predictive analytics techniques to build models that successfully predict a specific economic outcome, a goal that this study endeavors to accomplish.

Statistical procedures. According to Estrella (2005), researchers in the area of economic forecasting have relied on relatively standard regression models to make predictions. These regression models employ continuous variables such as GDP, industrial production, consumption and investment. He goes on to contend that when the objective is to predict recessions, however, the default methodology ought to be a probit or logit model. The logit model “is a technique which allows for estimating the probability that an event occurs or not, by predicting a binary dependent outcome from a set of independent variables” (Vasisht, p. VI-56). The probit model is similar to the logit model, except it uses the cumulative distribution function to determine the output, while the logit model uses the cumulative logistic function.

In both these models the forecasted variable only assumes the values one and zero, i.e., either the economy is in a recession or not. Nagler (1994), corroborates this assertion, suggesting that logit and probit models are the two most commonly employed techniques when the output is a categorical (dichotomous) dependent variable. Haltmaier (2008) also confirmed the usefulness of probit models in a study that examined the prediction of business cycles in seven countries.

According to Long (1997) the decision to select either a probit or a logit model is “largely one of convenience and convention, since the substantive results are generally indistinguishable” (p. 83). He goes on, however, to advise that probit models can be computationally demanding. To this end, models involving qualitative dependent variables are based on the probit model, while the logit model may be preferable at other times. Hamberg and Verständig (2009) found that a logistic regression model can be a helpful economic forecasting tool. They constructed a logistic-regression model that used the stock index, the yield spread, the confidence index, GDP, and residential building starts to predict turning points in the business cycle. Their model had an overall success rate of approximately 80%.

According to Vasisht (2010), the logit model:

1. produces “statistically sound” results (p. VI-58),
2. provides results which can “easily be interpreted because the method is easy to analyze” (p. VI-58), and
3. provides parameters estimates that are “consistent, efficient, and normal” (p. VI-58).

Vasisht’s (2010) conclusions provide strong support for the employment of the logit model in this study. Furthermore, this study analyzes quantitative variables. Hamberg and Verständig’s contention that probit models are better suited to analysis of qualitative dependent variables rather than quantitative dependent variables (2009) provides additional support for the

use of the logit model in this study. Finally, Hamberg and Verständig's successful parallel study that used the logit model to predict economic peaks and troughs further solidifies the merits of the logit model as a good fit for this study.

Literature Summary

An examination of the five distinct bodies of literature in this chapter yielded the following: (1) an operational definition of a recession, (2) confirmation of the forecastability of recessions, (3) an explication of the models and techniques currently employed in recession forecasting, a delineation of their strengths and weaknesses, the data and data sources that these models engage, and a sense of which model/technique exhibits the greatest level of stability, (4) an analysis of the gap in current forecasting models and techniques, (5) theoretical support for the inclusion of institutional policymaking activity as variables in forecasting models, (6) contextualization of institutional activity as an independent variable in economic analysis, along with the other variables that support forecasting of economic activity, and finally, (7) identification of statistical methods and processes that forecasters can employ to construct predictive models.

Chapter Three

Methodology

The purpose of this study is to augment the predictive power of conventional recession-forecasting models by examining the interrelationships among macroeconomic indicators, government information sources and performance data of public companies. Government information and corporate data are collectively referred to as institutional artifacts in this study. The study sought evidence of a predictive relationship between institutional artifacts and macroeconomic vulnerability, and then modeled these associations to provide long-range predictive insights to serve as a forewarning of impending recessions.

This chapter presents the research design that served as the framework for conducting this research study. Four unique categories of data are analyzed in this study: (1) Macroeconomic Indicators, (2) Company Financial Ratios, (3) Congressional Committee Hearings, and (4) Presidential Executive Orders. These datasets are examined for the three year duration preceding the recessions of 1973, 1981, 1990, and 2007. Specifically, data was analyzed for the following years:

- Analysis period 1 (three years preceding 1973): 1970, 1971, and 1972
- Analysis period 2 (three years preceding 1981): 1978, 1979, and 1980
- Analysis period 3 (three years preceding 1990): 1987, 1988, and 1989
- Analysis period 4 (three years preceding 2007): 2004, 2005, and 2006

The study explored the identified datasets, examined the interrelationships among their attributes, identified subsets of observations, and then used the resulting associations to construct

a predictive model that identified variables that are capable of predicting the odds of a recession by forecasting an inversion in the yield curve twelve months into the future. The yield curve inversion was selected as the dependent variable because, since 1960, a yield curve inversion (as measured by the difference between ten-year and three-month Treasury rates) has preceded every recession on record (Moench, 2008). A yield curve inversion also preceded the Great Depression. The concept map in Figure 8 outlines, at a high level, the methods employed to accomplish the stated outcomes.

Data Selection

The nature of the individual variables selected for analysis in this study was conceptualized in the literature review. This section identifies the variables, distinguishes the relationship among the variables, and describes the sample design for the selection of the different datasets.

Identification of dependent and independent variables.

- Dependent Variable: The yield spread (ten year rate minus three month rate)
- Independent Variables: Table 3 specifies and categorizes the independent variables analyzed in this study

Figure 8. Concept map of methods section

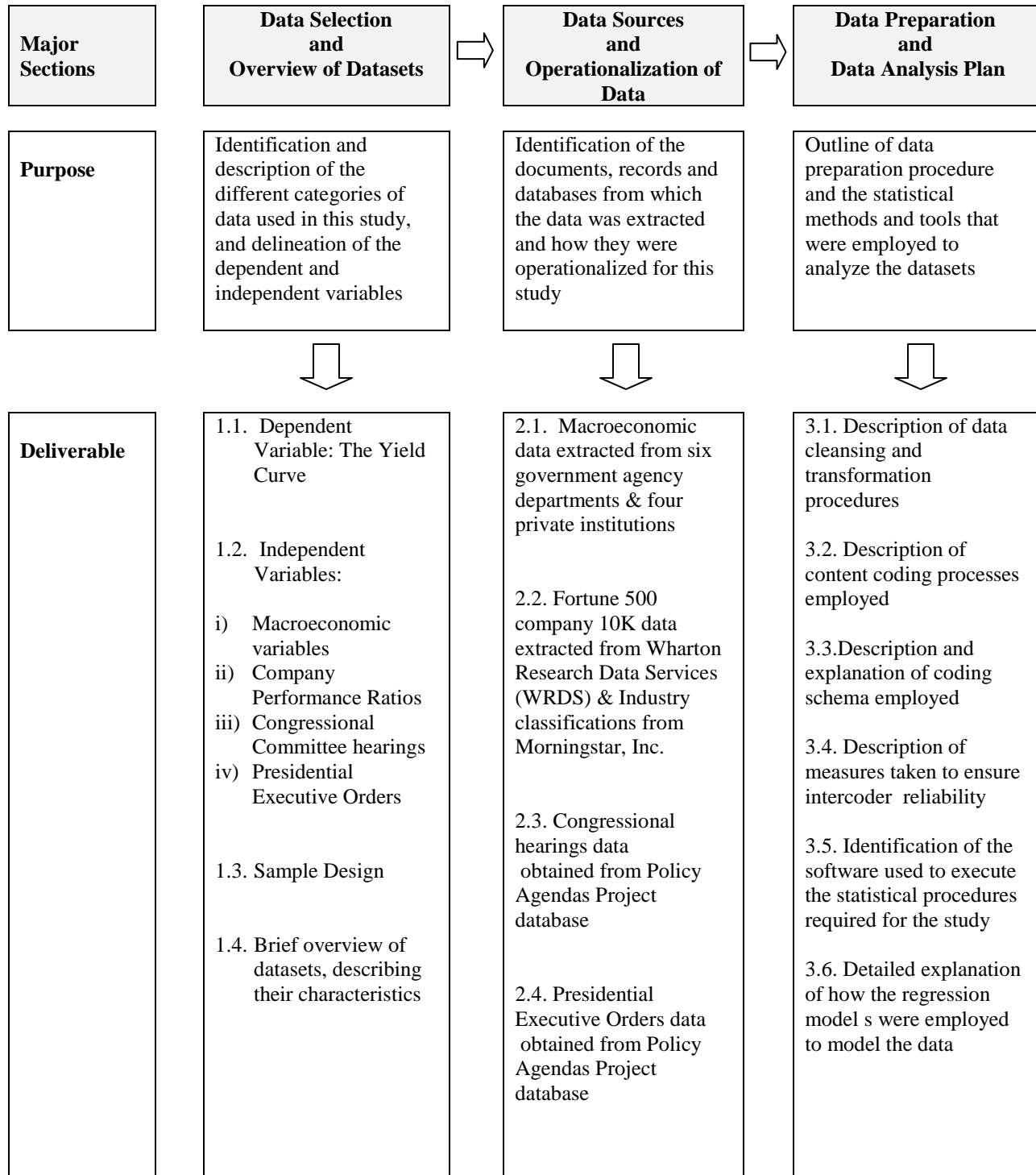


Table 3

Independent Variables

Macroeconomic Indicators	Financial Ratios	Government Data
<ul style="list-style-type: none"> • GDP • Leading Economic Index • Unemployment Rate • Industrial Production • Capacity Utilization • ISM New Orders Index • Housing Starts • Personal Income • Personal Outlays • Consumer Price Index • Producer Price Index • Consumer Confidence Index • Manufacturers' New Orders: Durables • Manufacturers' New Orders: Capital Goods • Advance Monthly Sales: Retail trade and food services • Consumer Sentiment Index 	<ul style="list-style-type: none"> • Current ratio • Total asset turnover • Total debt to assets • Times interest earned • Net profit margin • Return on assets 	<ul style="list-style-type: none"> • Congressional hearings • Executive orders

To facilitate more meaningful comparisons, the study employed the compounded rates of change rather than the actual monthly reported value for four macroeconomic indicators:

- Personal income
- Personal outlays
- Consumer Price Index (CPI)
- Producer Price Index (PPI)

Sample Design

Macroeconomic data. All macroeconomic indicators identified in Table 1 are published monthly, except for GDP, which is published quarterly. For each year included in the respective analysis periods, the entire set of data published that year was examined. The data set is limited to the macroeconomic indicators identified in Table 1. Consequently, no sampling technique was necessary to extract a specific data sample as far as these data was concerned.

Government information sources. For each year included in the respective analysis periods, the entire set of government information sources that relate exclusively to congressional hearings and executive orders published that year, was examined. The data set was limited to what was published at the discretion of the government for each year.

Fortune 500 company performance data. The population for this component of study was all companies listed on the U.S. Fortune 500 list for every year under examination. It was impractical to attempt to include all the companies on the U.S. Fortune 500 list for every year being examined because of the volume of data per period. To alleviate this problem, a probability sampling method was employed to draw a representative sample of U.S. Fortune 500 companies. A decision was made to examine a sample of twenty companies, which was deemed a reasonable dataset, given the parameters and constraints of this study.

An essential requirement of this study was that the corporations selected in the sample had to have been included in the U.S. Fortune 500 list, without exception, for every year under examination, namely, 1970, 1971, 1972, 1978, 1979, 1980, 1987, 1988, 1989, 2004, 2005, and 2006. To obtain an appropriate sampling frame, the Fortune 500 database was accessed (Fortune, 2010). This database contains 50 years of Fortune's list of America's largest corporations, displayed alphabetically. Every company in the database was inspected to ascertain whether it was included in the list for each of the years identified earlier. After a thorough mining of the database, a list of 97 companies fitting the required criterion was produced. This was an alphabetical list generated from the sequential inspection of the companies listed in the database. Each company was added to the list in the order that the companies were inspected. No other ordering of the data was conducted.

The next step required the selection of the sample population of twenty companies. To facilitate this process, a systematic sampling procedure, as detailed by Statistics Canada (the Government of Canada's Statistical Department), was employed:

1. Each entry in the sampling frame was numbered, starting at one and ending at 97.
2. The sampling interval was then determined by dividing the number of units in the population (97) by the desired sample size of 20. The resulting value of 4.85 was rounded up to 5. Therefore, to arrive at a total of 20 companies in the sample, one unit out of every five units was to be selected.
3. The next step required the selection of a number between one and five for the random start. The number four was selected at random. This number was the first number included in the sample.

4. Every fifth number on the sequential list was then selected after that first number, until 20 numbers were selected.
5. After the initial selection of 20 companies was made, a preliminary examination of the available datasets revealed that all the data required for analysis was not available for three companies in the selected sample. Step number 4 was then repeated, starting where the previous selection process ended, until these three companies were replaced in the sample.

Table 4 identifies the twenty companies included in the final list once the sampling procedure was completed. Also included in the table are the numbers assigned to each company based on their original positioning in consolidated list of companies.

Table 4

Representative Sample of Fortune 500 Companies by Sector and Industry

No.	Company Name	Sector	Industry
2	Abbott Labs	Healthcare	Drug Manufacturers - Major
4	Alcoa	Industrial Materials	Aluminum
9	Archer Daniels Midland	Consumer Goods	Farm Products
14	Cummins	Industrial Materials	Diversified Machinery

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Table 4 (continued)

No.	Company Name	Sector	Industry
19	Coca-Cola	Consumer Goods	Beverages - Softdrinks
24	Crown Holdings	Consumer Goods	Packaging and Containers
29	DuPont	Chemicals	Major-Diversified
34	Exxon Mobile	Energy	Major Integrated Oil & Gas
39	Hormel Foods	Consumer Goods	Meat Products
44	Goodrich	Industrial Materials	Aerospace/Defense Products & Services
49	Honeywell International	Industrial Materials	Aerospace/Defense Products & Services
54	Kellogg	Consumer Goods	Processed & Packaged Goods
64	Navistar International	Consumer Goods	Trucks and other vehicles
74	Pfizer	Healthcare	Drug Manufacturers - Major
79	Raytheon	Industrial Materials	Aerospace/Defense Major Diversified
84	Sunoco	Energy	Oil & Gas Refining & Marketing
89	Unisys	Technology	Information Technology Services
12	Becton Dickson	Healthcare	Medical Instruments and Supplies
17	Caterpillar	Industrial Goods	Farming and Construction Machinery
22	ConAgra Foods	Consumer Goods	Processed and Packaged Foods

The industry sector classification was based on the classification system used by Morningstar, Inc., a prominent global independent investment research provider. Morningstar is

an authoritative data source that is widely employed by leading financial institutions and investment corporations all over the world. The industry sector classifications are based on operational characteristics of the specific company.

The sample contains a broad representation of industries which includes companies that engage in a diverse array of operational activities such as healthcare services, biomedical research, oil and gas refining, information technology services, industrial goods production, and consumer goods production. Companies classified under consumer goods produce food, beverages, farm products, processed and packaged goods, packaging and containers, and motor vehicles. Companies classified under industrial goods include producers of lumber wood and manufacturers of heavy machinery, and aerospace and defense equipment. Because of the wide representation of different industries in the sample, the study results were more amenable to broader generalization.

Overview of Datasets

Macroeconomic indicators. The various departments and agencies of the U.S. federal government collect, compile and publish a wide variety of economic data. These published records are regarded as the most authoritative and definitive source of economic data pertaining to the nation's economic activities. Authoritative economic data is also published by private organizations such as The Conference Board and Institute for Supply Management. Table 4 details the individual microeconomic data variables that this study is concerned with, and provides a brief description of its nature.

Government information sources. Congressional hearings are reflective of the intensity of interest or activity in a particular policy area. Likewise, presidential executive orders are generally construed as an indicator of presidential priorities. Collectively, these institutional

artifacts highlight the level of government activity in a particular policy area. This study is concerned with the *number* of congressional hearings conducted and executive orders issued in the periods being analyzed.

The dataset does not include a comprehensive list of every congressional hearing or executive order issued by the president for the periods under review. The dataset was specifically compiled using the coding classification employed in the Policy Agendas Project (2010). Congressional hearings and executive orders relating to subject categories outside those identified in Table 5 below were eliminated from the dataset.

Table 5

Subject categories for executive orders

Major Subject Category	Sub Categories
Macroeconomics	<ul style="list-style-type: none"> • National Budget and Debt • Price Control and Stabilization • Inflation, Prices and Interest rates • Monetary Supply, Federal Reserve Board, and the Treasury • General domestic macroeconomic issues
Banking, Finance & Domestic Commerce	<ul style="list-style-type: none"> • General banking, finance and domestic commerce • Consumer finance, mortgages and credit cards • Securities and commodities regulation • Small business issues
Foreign Trade	<ul style="list-style-type: none"> • Productivity and competitiveness of US businesses, US balance of payments • Export promotion and regulation • Tariff and import restrictions and regulation • International Private Business Investments, Overseas Private Investment Corporation (OPIC) • Trade Negotiations, Disputes, and Agreements

Congressional committee hearings. The hearings dataset included information on all congressional hearings conducted between 1947 and 2006. The data was obtained from the hearings sections in the Congressional Information Service /Annual: Abstracts of Congressional Publications and Legislative History Citations. Included in the Congressional Information Service (CIS) publication are the hearings of committees, subcommittees, task forces, panels and commissions, and the joint committees of Congress. Those entries in the CIS publication's hearings section that were not actually hearings were not coded and included in this dataset. Examples of these include publications, supplementary materials, and declassified materials (Policy Agendas Project, 2010).

Presidential executive orders. The executive orders dataset included information about each executive order issued between 1945 and 2003. More than 3,800 records are coded in the databases. Each order is coded using the coding frame established by the Policy Agendas Project. For this study, complete, coded data were available for three periods, namely:

1. 1970, 1971, 1972
2. 1978, 1979, 1980
3. 1987, 1988, 1989

Fortune 500 company performance data. Public companies are required by law to file an annual report with the Securities and Exchange Commission (SEC) on Form 10-K. This is the definitive record of a company's financial and operational performance in a particular fiscal year. The Form 10-K includes, inter-alia, audited financial statements, a review of operations, and management discussion and analysis. The audited financial statements included in the filings highlight the company's assets, liabilities and earnings per share. The data presented in the financial statements was used to compute company performance data.

Company performance was assessed via ratio analysis. Ratio analysis helps put into perspective a specific company's operational performance, its solvency or financial position, and the efficiency with which its resources are being employed. The ratios were computed using formulas identified in Table 6.

Table 6

Performance ratios formulas and explanation of measurement

Ratio	Formula	What is being Measured
Current ratio	Total Current Assets / Total Current Liabilities	The liquidity of the company
Total asset turnover	Revenue / Total Assets	Revenue generated for every dollar of assets on hand
Total debt to assets	Total Liabilities / Total Assets	The extent to which the firm is using long term debt
Times interest earned	Earnings before Interest & Tax / Interest Expense	A company's ability to meet interest payments
Net profit margin	Net Income / Net Sales	Net income generated from each dollar of sales
Return on assets	Net Income / Total Assets	Company's capacity to use assets to generate profits
Return on equity	Net Income / Equity	Income earned on investors capital
Price-To-Earnings	Market Value per Share / Earnings per Share	How much investors are willing to pay per dollar of earnings
Book-To-Market	Book Value of Firm / Market Value of Firm	Whether the stock is overvalued or undervalued

Data Sources and Operationalization

Table 7 provides a summary of the individual data variables that this study is concerned with; reiterates, at a high level, its nature; identifies the source from which this data was extracted; indicates how often the data is published; and finally, explains how the data variable was operationalized for this study.

Table 7

Data sources and operationalization

Data Variables	Nature of Variable	Source of Data Extraction	Frequency of Publication	How Data was Operationalized for this Study
<i>Macroeconomic Data</i>				
Gross Domestic Product	Measures total dollar value of all goods and services produced over a quarter	U.S. Bureau of Labor Statistics: National Economic Accounts	Quarterly	Percentage increase or decrease over the previous quarter
Leading Economic Index	Derived from the individual leading economic indicators that precede the change in the business cycle, e.g. stock market returns	Bloomberg Terminal	Monthly	Actual index value as published
Unemployment Rate	A measure of the number unemployed as a percent of the labor force	Economagic	Monthly	Actual value as published
Industrial Production	A measure of wholesale prices at the producer level for consumer goods and capital equipment.	Board of Governors of the Federal Reserve System	Monthly	Actual value as published
Capacity Utilization	Measures the extent to which U.S. manufacturing companies make use of their factories and machinery	Board of Governors of the Federal Reserve System	Monthly	Actual value as published

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Table 7 (continued)

Data Variables	Nature of Variable	Source of Data Extraction	Frequency of Publication	How Data was Operationalized for this Study
New Orders Index	Reflects the health of the manufacturing sector by measuring the levels of new orders from customers	Institute for Supply Management	Monthly	Actual value as published
Housing Starts	Measures the number of housing units on which construction was started	U.S. Dept. of Housing and Urban Development	Monthly	Actual value as published
Personal Income	<i>Measures the total income</i> received by all persons from all sources	Federal Reserve Bank of St. Louis	Monthly	Compounded rate of change from one period to another
Personal Outlays	Measures total consumption expenditures on durable goods, nondurable goods and services.	U.S. Dept. of Commerce: Bureau of Economic Analysis	Monthly	Compounded rate of change from one period to another
Consumer Price Index	Measures inflation, i.e., how much the price of a basket of consumer goods has changed over a given time period	U.S. Bureau of Labor Statistics: Consumer Price Index	Monthly	Compounded rate of change from one period to another
Producer Price Index	A measure of wholesale prices for consumer goods and capital equipment at the producer level	U.S. Bureau of Labor Statistics: Producer Price Index	Monthly	Compounded rate of change from one period to another

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Table 7 (continued)

Data Variables	Nature of Variable	Source of Data Extraction	Frequency of Publication	How Data was Operationalized for this Study
Consumer Confidence Index	Measures the degree of enthusiasm that consumers demonstrate about the state of the economy as expressed through savings and spending	Bloomberg Terminal	Monthly	Actual Index Value as published
Manufacturers' New Orders: Durables	Measures new orders received from manufacturers of durable goods, e.g. manufacturers of motor vehicles	U.S. Dept. of Commerce: Census Bureau	Monthly	Actual value as published
Manufacturers' New Orders: Capital Goods	Measures new orders received from manufacturers of capital goods, e.g. manufacturers defense equipment	U.S. Dept. of Commerce: Census Bureau	Monthly	Actual value as published
Advance Monthly Sales: Retail and Food Services	Measures early monthly sales of companies in the retail trade and food services	U.S. Dept. of Commerce: Census Bureau	Monthly	Actual value as published
Consumer Sentiment Index	Measures consumers' confidence in the economy	University of Michigan	Monthly	Actual value as published

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Table 7 (continued)

Data Variables	Nature of Variable	Source of Data Extraction	Frequency of Publication	How Data was Operationalized for this Study
<i>Government Information Sources</i>				
Congressional Hearings	Proceedings of hearings of committees & sub-committees	Policy Agendas Project	Monthly	Hearings related to topic categories extracted and counted: <ul style="list-style-type: none"> • Macroeconomics • Banking, Finance, and Domestic Commerce • Foreign Trade Value expressed as a number per month
Executive Orders	Record of Executive Orders issued by the President	Policy Agendas Project	Monthly	Hearings related to topic categories extracted and counted: <ul style="list-style-type: none"> • Macroeconomics • Banking, Finance, and Domestic Commerce • Foreign Trade. Value expressed as a number per month

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Table 7 (continued)

Data Variables	Nature of Variable	Source of Data Extraction	Frequency of Publication	How Data was Operationalized for this Study
<i>Fortune 500 Company Data</i>				
Total Current Assets	A measure of the cash, accounts receivable, inventory and supplies (assets that can be converted into cash)	Wharton Research Data Services	Annually	Actual annual dollar value as reported
Total Current Liabilities	A measures of the sum of accounts payable, accrued liabilities and taxes (debts of the company)	Wharton Research Data Services	Annually	Actual annual dollar value as reported
Revenue	A measure of the amount of money a company receives from its activities	Wharton Research Data Services	Annually	Actual annual dollar value as reported
Total Assets	A measure of the sum of current and long terms assets owned by a company	Wharton Research Data Services	Annually	Actual annual dollar value as reported
Total Liabilities	A measure of the sum of current and long term liabilities of a company	Wharton Research Data Services	Annually	Actual annual dollar value as reported
Earnings before Interest and Tax	A measure of a company's ability to generate income from its operations	Wharton Research Data Services	Annually	Actual annual dollar value as reported

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Table 7 (continued)

Data Variables	Nature of Variable	Source of Data Extraction	Frequency of Publication	How Data was Operationalized for this Study
Interest Expense	A measures of the cost of company borrowings	Wharton Research Data Services	Annually	Actual annual dollar value as reported
Net Income	A measure of the company's earnings after depreciation, interest, taxes and other expenses are taken into account	Wharton Research Data Services	Annually	Actual annual dollar value as reported
Net Sales	A measure of the amount of sales generated by a company after returns, discounts, damages, and other allowances are accounted for	Wharton Research Data Services	Annually	Actual annual dollar value as reported
Equity	A measure of a company's total assets minus its total liabilities	Wharton Research Data Services	Annually	Actual annual dollar value as reported
Market Value per Share	A measure of a company's assessed market value divided by the total number of shares held by shareholders	Wharton Research Data Services	Annually	Actual annual dollar value as reported

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Table 7 (continued)

Data Variables	Nature of Variable	Source of Data Extraction	Frequency of Publication	How Data was Operationalized for this Study
Earnings per Share	A measure of the total profits of a company divided by the number of outstanding shares of common stock	Wharton Research Data Services	Annually	Actual annual dollar value as reported
Book Value of Firm	A measure of the total value that shareholders would theoretically receive if a company was liquidated	Wharton Research Data Services	Annually	Actual annual dollar value as reported
Market Value of Firm	A measure determined by multiplying the total number of a company's outstanding shares by the current price of its shares.	Wharton Research Data Services	Annually	Actual annual dollar value as reported

Macroeconomic data. Microeconomic data was extracted from multiple sources for two reasons:

- government portals don't always publish historical data going back to the seventies and eighties
- four of the macroeconomic variables identified are published by non-governmental agencies

Company financial data. EDGAR, the U.S. Securities and Exchange Commission's official Electronic Data Gathering, Analysis, and Retrieval system, performs automated collection, validation and indexing of filings by companies (U.S. Securities and Exchange Commission, 2010). However, the Securities and Exchange Commission did not always require companies to file Form 10-K electronically. Electronic filing became a requirement since 1993. The EDGAR database makes electronic filings available from 1994 onwards. Given that three of the four recession periods being investigated are pre-1994, the EDGAR information database service was rejected as a potential data source for company filings.

Wharton Research Data Services (WRDS), a web-based business data research service provider from The Wharton School of the University of Pennsylvania is the data source from which the company SEC filings were obtained. This database offers a comprehensive, searchable database for company and industry information, including regulatory filings. Unlike the EDGAR database, WRDS provides historical data for the entire period under examination. WRDS was selected because of its authority, ease of use, and accessibility. The database is extensively employed in research studies.

Government information sources. The Policy Agendas Project is an online resource portal that provides a record of all government activity across all policy issues since World War II (Policy Agendas Project, 2010). The fifteen-year-old project was funded by the National Science Foundation. Dr. Frank Baumgartner, one of the founding directors of the project, describes it as “an attempt to provide comparable measures of policy changes since the 1940s” (para. 4). Baumgartner further explains that this effort was inspired by the fact that:

The state of the economy has been the only field that has been historically tracked. Other than that, there have never been a valid or reliable set of measurements for all other social issues and public policy....Just as it is important to track changing economic conditions and policies, which government has tracked systematically for decades, so too is having knowledge about other, non-economic issues. Through these data, we can see if government policy shifts are more responsive to public opinion, to shifting societal conditions, or to interested lobbying groups, for example (Topic tracking, 2007, para. 4).

Included in The Policy Agendas Project are congressional House, Senate, and Joint hearings data, and the presidential documents. This resource is unique in that it is not just a repository for institutional data, but that it is a repository for institutional data that has already been coded. The coding frame is very comprehensive and the coding categories are mutually exclusive. The data coding has been conducted in manner that postures the dataset optimally for this project. By categorizing the data into a major topic, and further categorizing it into a subtopic, it allows for analysis to be conducted at a relatively high level of aggregation or a lower, more specific, level of aggregation (Baumgartner, Jones and Macleod, 2008). Along with the year classification, the major topic and subtopic categories also facilitate expedient navigation of the coded data. The year category identifies the year in which the action covered in the document was initiated. The major topic category is the general content code for the predominant policy area covered. The subtopic category is the detailed content code for the predominant policy area covered. These categories make it possible to effectively reduce the

extensive datasets to smaller, relevant datasets that inform this study. Identification variables link the records to the original Congressional Information Service (CIS) source documents published by the government.

Data Preparation

Data preparation activities to sanitize and reformat data for model creation involved identifying and extracting the data; checking the data for accuracy; checking the data for any outliers; developing a database structure for collecting and storing the data; and transforming the data for input into the data mining software application.

Macroeconomic data.

Data extraction. The macroeconomic data was obtained from a number of different sources. The data was downloaded from these external data sources into a composite MSEXcel spreadsheet.

Data cleansing. Data was downloadable in the required format. No data cleansing was required.

Content coding. Macroeconomic data did not require content coding.

Coding schema. Macroeconomic data did not require a coding schema.

Congressional hearings.

Data extraction. The text files were downloaded from The Policy Agendas Project website into an excel file.

Data cleansing. The datasets provided in the Policy Agendas Project database is in tab delimited text format. When the required datasets were downloaded as MSEXcel files, the data did not appear in clearly discernible columns, which made it difficult to analyze. To ensure that the data was in the required format, specific import settings were defined in the text import

wizard before the file was imported from the external database. A series of data cleansing and data transformation steps were required to prepare the data for analysis.

Content coding. The policy content of the proceedings and other critical variables were the basis for the content coding of all hearings. The coders employed 19 major topic codes and 225 subtopic codes in the policy content coding. Examples of two major topics and their accompanying subtopic categories are illustrated in table 5 below:

Table 8

Example of content coding categories

Major Topic	Subtopic
Macroeconomics	<ul style="list-style-type: none"> • Inflation, Prices, and Interest Rates • Unemployment Rate • Monetary Supply, Federal Reserve Board, and the Treasury • National Budget and Debt
Energy	<ul style="list-style-type: none"> • Nuclear Energy and Nuclear Regulatory Commission Issues • Electricity and Hydroelectricity • Natural Gas and Oil

To facilitate effective time-series research of a specific topic, each hearing was assigned only one exclusive major content code. This makes it expedient for a researcher to trace hearing activity on a particular topic across a particular period.

Coding schema. A detailed coding schema is provided by the Policy Agendas Project (2010). The schema provides a brief description of each data column, as well as an explanation of the coding rules for the data collected. The data columns that are of interest in this study are:

1. Year: The year on which the hearing started

2. Majorname: The major topic that the policy issue is classified under.
3. Subtopic: The subtopic that the policy issues is classified under
4. Topic Description: A description of the topic entry

Presidential executive orders.

Data extraction. The text files were downloaded from The Policy Agendas Project website into an excel file.

Data cleansing. The datasets provided in the Policy Agendas Project database is in tab delimited text format. When the required datasets were downloaded as MSExcel files, the data did not appear in clearly discernible columns, which made it difficult to analyze. To ensure that the data was in the required format, specific import settings were defined in the text import wizard before the file was imported from the external database. A series of data cleansing and data transformation steps were required to prepare the data for analysis.

Content coding. The policy content of the executive orders was coded using 25 content categories. Similar to the coding of congressional committee hearings, the coders employed 19 major topic codes and 225 subtopic codes in the policy content coding. Examples of the major topic codes and the subtopic codes are furnished in the previous sub-section. By employing the same topic codes (major and sub-) in the content coding of congressional hearings and executive orders, consistency in the datasets is promoted and useful comparative analyses is facilitated.

Coding schema. A detailed coding schema is provided by the Policy Agendas Project (2010). The schema provides a brief description of each data column, as well as an explanation of the coding rules for the data collected. The data columns that are of interest in this study are:

1. Year: The year in which the executive order was issued
2. Majorname: The major topic that the policy issue is classified under.

3. Subtopic: The subtopic that the policy issues is classified under
4. Topic Description: A description of the topic entry/record

Fortune 500 company data.

Data extraction. The Wharton Research Data Services (WRDS) database provided sophisticated data selection and download functionality for users. This facilitated expedient data downloads in the required format, which in this case was in MSExcel format. The data for each company was saved in a separate worksheet within the spreadsheet. Formulae were embedded in each worksheet to compute the financial ratios for the respective companies. Validation formulae were also used as an additional measure to ensure that no inconsistencies manifested once the computations of the ratios were completed.

Data cleansing. Data was downloadable in the required format. No data cleansing was required.

Content coding. Company financial data did not require content coding.

Coding schema. Company financial data did not require a coding schema

Reliability.

Right at the outset, meticulous coding and reliability standards were imposed in the coding process. The following discussion summarizes the measures taken to ensure reliability, as furnished by Baumgartner, Jones and Macleod (2008), the originators and directors of the Policy Agendas Project.

The first strategy to ensure reliability was to train a small number of highly skilled people to understand the coding processes in acute detail. This allowed the project directors to then appoint a larger pool of coders who did not need to be as extensively trained, and whose work would not involve making any sort of complicated coding decisions. The coding frame employed

very simple coding rules combined with a coding process that ensured that the data entry personnel were closely supervised by a group of highly trained coders who were well versed with the coding mechanism. This fostered a much greater level of reliability as would have been the case if each coder had worked independently and unsupervised.

To ensure intercoder reliability, which was a real threat given the large number of coders working on the project, two highly trained expert coders were responsible for all major topic and subtopic assignments. The assigned codes were then validated by another set of expert coders. To ensure intercoder reliability between the two experts, each of them separately assigned topic codes to the same entries. The project directors met with the expert coders weekly to resolve differences and refine the codebook. The expert coders were only allowed to work on their own after reliability scores above 90% for the major topics and 70% for the subtopics were established. Within the first two years, reliability scores rose from 85% to 95% on the major topics and from about 65% to 90% on the subtopics, based on periodic tests of 100 cases.

Cohen's kappa, is a statistical measure of the agreement between two raters who each classify N items into C mutually exclusive categories (Smeeton, 1985). According to Landis and Koch (1977), if the value of Cohen's kappa is between .81 and 1.00, this implies complete agreement between the raters. The reliability scores of .95 and .90, respectively, suggest a significantly high level of agreement between the raters.

Periodic reliability checks and weekly meetings ensured that the codebook was appropriately revised. As a case in point, after 10,000 hearings were complete, they were sorted by topic and the reviewers validated each entry for correctness, and inconsistencies were rectified. The probability of assigning an incorrect categorization code was an ever-present reality. To manage this risk, a short written description of each record in each dataset was

inserted next to the topic code. This provides a way for a researcher using the datasets to validate the categorization codes, and make any changes if there is difference of opinion.

Data Analysis Plan

The data collected for the study had two dimensions: a spatial dimension that pertained to a set of cross-sectional units of observation, and a temporal dimension that pertained to periodic observations of a set of variables characterizing these cross-sectional units over a particular time span. The data analysis plan involved:

1. merging the different datasets into the required format for analysis
2. building the model using competitive algorithms to search for a combination of data that reliably predicted the outcome

Data merging. The prepared datasets constituted from the four different data categories initially resided in a comprehensive excel workbook. Once all the data was ready for manipulation, the individual datasets were merged into a specific format for analysis. This necessitated the writing of specific code to execute the merge function in the software application.

Statistical procedures.

Simple OLS regression and multiple regression. Simple ordinary least squares regression and multiple regression analyses were employed to model the relationships between the independent variables and the dependent variable (yield spread). Simple regression analysis was initially run to identify which of the independent variables, if any, predicted the value of the yield spread (dependent variable). Simple regression was run because there were too few data points to run multiple regression analysis on performance data for public corporations, and quarterly macroeconomic data.

To control for multicollinearity between the independent variables, a Pearson's correlation matrix was run and the results were examined for significant associations. Pairwise correlations with R-square values greater than 0.8 were further evaluated and, to mitigate potential problems with multicollinearity, two independent variables were dropped. Multiple regression analysis was then run to ascertain how well each independent variable predicted the dependent variable, controlling for the mediating effect of other variables.

Logistics regression. A conceptualization of logistic-regression is presented in the literature review. The logistic regression model or logit model is used to predict the probability of occurrence of an event by fitting data to a logit function (Murphy, 2010). The model for logistic-regression analysis assumes that the outcome variable, Y, is binary. This means that there are only two possible outcomes, e.g. "Yes" or "No." Since the probability of a response is being predicted, there is a zero to one scale: Y takes on the value of one when the outcome is positive (or a success) and zero when the outcome is negative (or a failure). In logistic-regression models, probabilities are transformed to odds, which are then transformed to log of odds. The rationale behind this is as follows (UCLA Academic Technology Services, 2010):

It is usually difficult to model a variable which has restricted range, such as probability. Probability ranges from zero to one, while odds range from zero to positive infinity. Odds increase as the probability increases and vice versa. By that same token, the greater the odds, the greater the natural logarithm of the odds (i.e., the log-odds). The transformation from probability to odds to log of odds is an attempt to get around the restricted range problem. Probability ranging between zero and one is transformed to log-odds ranging from negative infinity to positive infinity, eliminating the restricted range. This transformation is called logit transformation. The logistic regression model then allows us to establish a relationship between

the binary outcome variable and a group of predictor variables. It models the logit-transformed probability as a linear relationship with the predictor variables.

More formally, if Y is the binary outcome variable with failure = 0, and success = 1, and P is the probability of Y to be 1, then $p = \text{prob}(Y = 1)$. Let X_1, \dots, X_n be a set of predictor variables. Then the logistic regression of Y on X_1, \dots, X_n estimates parameter values $\beta_0, \beta_1, \dots, \beta_n$. The probability of an event occurring (“1”) can then be computed by first plugging the predictor variables (X_n) and the parameter values (β_n) in the following formula:

$$\text{logit}(p) = \log(p/(1-p)) = \beta_0 + \beta_1 * X_1 + \dots + \beta_n * X_n$$

Thereafter, $\text{logit}(p)$ is translated by expressing it to base e to obtain the probability of the event occurring:

$$p = \exp(\beta_0 + \beta_1 * X_1 + \dots + \beta_n * X_n) / (1 + \exp(\beta_0 + \beta_1 * X_1 + \dots + \beta_n * X_n)) \quad (\text{Meier \& Balke, 2006; Hailu \& Regassa, 2007})$$

The outcome variable for the logistics regression analysis for this study was the yield spread (dependent variable). Since the output variable is binary in logit models, the model only contained data that was coded as $Y=1$ (YES, a recession is predicted) or $Y=0$ (NO, a recession is not predicted). The basis for coding the data in the model was grounded in the empirical literature reviewed. According to Moench (2008), a yield curve inversion (as measured by the difference between ten-year and three-month Treasury rates) has preceded every recession on record since 1960, and has thus proven to be robust over time. A yield curve inversion occurs when long-term yields fall below short-term, i.e., the difference between ten-year and three-month Treasury rates falls below zero percent. Even though Estrella and Mishkin’s analysis of yield spreads found that spreads smaller than 1.21 percent predicted greater probabilities of recessions one year forward (1996), the more aggressive level of zero percent was selected for

this model. This was done to minimize the risk of conducting a Type I error (not predicting a recession that actually occurs), or a Type II error (predicting a recession that does not occur). The logit model was thus coded to predict the probability of a recession if the yield spread inverted (value of the spread became negative).

Interpreting the model. Logistics regression models do not model the binary outcome variable ($Y=1$ or $Y=0$) directly. Rather, they model probabilities associated with the values of Y (Dayton, 1992). The importance of each variable is determined by assessing the statistical significance of the coefficient of that variable. A positive regression coefficient indicates that an increase in the predictor variable increases the probability of the outcome, while a negative regression coefficient indicates that an increase in the predictor variable decreases the probability of that outcome.

Statistical tool. The analysis software SAS was the analytical tool employed for statistically analyzing the data in this study. SAS software employs a simplified data mining process to create highly accurate predictive and descriptive models. The software is widely used by corporations and academics to model economic and operational data. James Kobielus, a senior analyst at Forrester Research Inc., asserts that SAS has “comprehensive feature-rich modeling/mining and statistical analysis tools for mining complex structured and unstructured information” (2010, para. 2). A salient strength of the software is its highly interactive statistical and visualization tools that facilitate a more expedient search for trends and anomalies, thereby supporting the model development process. MSExcel files are compatible with SAS and were uploaded into the application for analysis.

Summary

Four unique datasets were analyzed in this study: (1) Macroeconomic Indicators, (2) Company Financial Ratios, (3) Congressional Committee Hearings, and (4) Presidential Executive Orders. This chapter commenced with identifying the variables selected, distinguishing the dependent and independent variables, and describing the sample design for the selection of the various datasets. Thereafter, a brief overview of the respective datasets was furnished.

Authoritative data sources from which the data was extracted were then identified, as well as how these individual data was operationalized for this study. The primary data sources consulted for extracting macroeconomic indicators were the various departments and agencies of the U.S. Federal Government, The Conference Board, the Institute for Supply Management, and the University of Michigan. Wharton Research Data Services (WRDS), a web-based business data research service provider from The Wharton School of Business at the University of Pennsylvania was employed as the definitive source for Fortune 500 company financial data. And, finally, for government institutional activity, The Policy Agendas Project served as the data source. The Policy Agendas Project is an online research repository that provides coded datasets of government policymaking activity across all policy issues for over five decades (Policy Agendas Project, 2010). The coding frame is very comprehensive, and the content coding has been conducted in a manner that postures the dataset favorably for this project.

The description of the methodology went on to include the steps taken to prepare the data for analysis. The data preparation steps involved identifying and extracting the data; checking the data for accuracy; developing a database structure for collecting and storing the data; and cleansing and transforming the data for input into the data mining software application. Included

in the data preparation section was an exposition of the content coding processes and the specific coding schema employed, along with how reliability was ensured. Data preparation was greatly minimized for congressional hearings and presidential executive orders because the data was already coded.

Finally, a detailed data analysis plan was furnished, along with the specific statistical procedures that were employed in the study. SAS was the software tool used to perform the statistical analysis, and regression analysis was used to model the relationship between the dependent and independent variables.

Chapter Four

Results

The purpose of the study is to augment the predictive power of conventional recession-forecasting models by examining the interrelationships among macroeconomic indicators, government information sources, and performance data of public companies. Government information and corporate data are collectively referred to as institutional artifacts in this study. The study sought evidence of a predictive relationship between institutional artifacts and macroeconomic vulnerability, and then modeled these possible associations to provide long-range predictive insights to serve as a forewarning of impending recessions.

The previous chapter presented the methodology employed to model the relationships between macroeconomic indicators, government information sources and performance data of public companies, and the yield spread. The description of the methodology began with the steps taken to prepare the data for analysis, and an exposition of the content coding processes and the specific coding schema employed, along with how reliability was ensured. A detailed data analysis plan was then furnished, along with the specific statistical procedures that were employed in the study. SAS was the software tool used to perform the statistical analysis, and regression analysis was used to model the relationship between the dependent and independent variables. Simple regression analysis was first used to model the relationships between the dependent variable (the yield spread) and the independent variables to assess which variables predicted the yield spread. Thereafter, to control for the mediating effect of one independent variable on another, multiple regression analysis was employed. The statistically significant

predictor variables emerging from the multiple regression analysis served as parameters for the logistic regression model. This chapter presents the results of the statistical analysis.

Ordinary Least Squares Regression

Ordinary least squares regression was employed to model the relationships between the independent variables and the dependent variable (yield spread). The results of the analysis are reported in Tables 10 and 11, and the following key outputs are distinguished:

- *F* value: Answers the question of whether the independent variable reliably predicts the dependent variable.
- Adjusted *R*-Square: Describes the proportion of variance in the dependent variable (yield spread) which can be predicted from the independent variable.
- *T*-Statistic: Is a measure of the statistical significance of the independent variable in explaining the dependent variable (yield spread).

Interpretation of the T-Statistic. To interpret the results of the analysis, the significance of the *T*-statistic was considered. Table 9 identifies the significance level corresponding with the respective *T*-statistic, and a brief statement of how the result was interpreted.

Table 9

Interpretation of the T-statistic

Significance Level	Meaning of <i>T</i> -statistic	Interpretation ¹
0.01	If <i>T</i> -statistic is > or = to 2.57, then there is a 1% chance that the variable does NOT predict the yield spread	<i>Very strong</i> evidence against the null hypothesis
0.05	If <i>T</i> -statistic is > or = to 1.96, then there is a 5% chance that the variable does NOT predict the yield spread	<i>Moderate</i> evidence against the null hypothesis
0.10	If <i>T</i> -statistic is > or = to 1.65, then there is a 10% chance that the variable does NOT predict the yield spread	<i>Marginal</i> evidence against the null hypothesis
0.20	If <i>T</i> -statistic is > or = to 1.28, then there is a 20% chance that the variable does NOT predict the yield spread	<i>Little</i> evidence against the null hypothesis

Simple regression. Simple regression analysis was employed to model the relationships between the independent variables and the dependent variable (yield spread). The key outputs are identified in Tables 10 and 11.

Table 10
Results of simple regression (Dependent variable: yield spread)

Variable	Panel A – Actual Data				Panel B – Rate of Change			
	<i>F</i> Value	Pr < <i>F</i>	Adj R-Square	<i>T</i> Value	<i>F</i> Value	Pr < <i>F</i>	Adj R-Square	<i>T</i> Value
Leading Economic Index	23.63	<0.0001	0.1409	10.73	2.35	0.1284	0.0121	1.53
Unemployment Rate	1.52	0.2202	0.0037	1.23	1.09	0.2979	0.0007	-1.05
Industrial Production	0.16	0.6882	-0.0061	-0.40	1.65	0.2013	0.0050	1.28
Capacity Utilization	16.76	<0.0001	1.1025	-4.09	2.48	0.1179	0.0113	1.57
ISM New Orders Index	16.46	<0.0001	0.1007	4.06	0.09	0.7705	-0.0071	0.29
Housing Starts	5.08	0.0259	0.0287	2.25	1.27	0.2611	0.0021	1.13
Personal Income*					2.00	0.1594	0.0072	-1.41
Personal Outlays*					0.54	0.4627	-0.0033	-0.74
Consumer Price Index*					20.04	<0.0001	0.1213	-4.48
Producer Price Index*					0.06	0.8078	-0.0069	0.24
Consumer Confidence Index	0.43	0.5147	-0.0048	0.65	0.09	0.7164	-0.0094	0.30
Mnfrs. New Orders Durables	116.56	<0.0001	0.7779	-10.80	0.00	0.9956	-0.0345	-0.01
Mnfrs. New Orders Consumer Goods	220.76	<0.0001	0.8694	-14.86	0.04	0.8371	-0.0330	0.21

*Note.**Represents compounded rate of change

Table 10 (continued)

Variable	Panel A – Actual Data				Panel B – Rate of Change			
	<i>F</i> Value	Pr < <i>F</i>	Adj. <i>R</i> - Square	<i>T</i> Value	<i>F</i> Value	Pr < <i>F</i>	Adj. <i>R</i> - Square	<i>T</i> Value
Advance Monthly Sales Retail	485.49	<0.0001	0.9362	-22.03	0.50	0.4849	-0.0169	0.71
Consumer Sentiment Index	31.73	<0.0001	0.2298	5.63	0.05	0.8316	-0.0100	0.21
Gross Domestic Product	0.01	0.9148	-0.0220	0.11	1.70	0.2000	0.0163	1.30
Congressional Hearings	0.61	0.4374	-0.0029	-0.78	0.16	0.6881	-0.0070	-0.40
Executive Orders	1.20	0.2762	0.0019	-1.09	1.24	0.2702	0.0051	-1.12
Current Ratio	0.16	0.7028	-0.1363	0.40	6.36	0.1278	0.6411	2.52
Total Asset Turnover	1.09	0.3370	0.0125	-1.04	0.31	0.6341	-0.2992	-0.56
Total Debt to Assets	0.00	0.9530	-0.1659	-0.06	4.41	0.1706	0.5138	-2.10
Times Interest Earned	0.48	0.5133	-0.0798	0.69	2.28	0.2704	0.2984	1.51
Profit Margin on Sales	0.01	0.9317	-0.1651	-0.09	0.02	0.9082	-0.4873	-0.13
Return on Assets	1.29	0.2991	0.0400	-1.14	0.00	0.9913	-0.4999	0.01
Return on Equity	0.44	0.5298	-0.0862	-0.67	0.07	0.8182	-0.4504	-0.26
Price Earnings Ratio	1.28	0.3018	0.0379	1.13	0.10	0.7832	-0.4295	0.31
Market to Book	3.03	0.1321	0.2252	1.74	0.11	0.7683	-0.4195	0.34

Table 11 summarizes the statistically significant results were observed in Table 10:

Table 11

Statistically significant results from simple regression analysis

Variable	Level of Significance
Leading Economic Index	$p < 0.01$
Capacity Utilization	$p < 0.01$
ISM New Orders	$p < 0.01$
Housing Starts	$p < 0.05$
Consumer Price Index (Compounded rate of change)	$p < 0.01$
Advance Monthly Sales Retail	$p < 0.01$
Consumer Sentiment Index	$p < 0.01$
Manufacturers' New Orders Durables	$p < 0.01$
Manufacturers' New Orders Consumer Goods	$p < 0.01$
Current Ratio	$p < 0.05$
Total Debt to Assets	$p < 0.05$
Market to Book	$p < 0.10$

Forty five percent of the independent variables predict the yield spread within a confidence range of 99% and 95%, respectively. Eight of the 11 independent variables predict the yield spread within a significance level of 0.01, suggesting that there is only one chance in 100 that these respective findings are not true. Three independent variables predict the yield spread within a level of significance of 0.05, suggesting that there is just five chances in 100 that these respective finding are not true. Collectively, the levels of significance connote moderate to

very strong evidence against the null hypothesis (H_0 : Independent variable does not predict the yield spread).

The p -values associated with nine of the twelve F -ratios are less than 0.0001, suggesting that the null hypothesis (H_0 : Model has no predictability) can be rejected. Therefore, these independent variables reliably predict the yield spread. Six of the 11 predictor variables have adjusted R -square scores that exceed 50%.

Overall, the values of the adjusted R -squares convey that the model is largely a good fit for the data. Advanced Monthly Retail Sales explains 94% of the variability of the yield spread, while Manufacturers' New Orders for Durables and Consumer Goods explain 78% and 87% of the variability of the yield spread, respectively. The Current ratio and Total Debts to Assets explains 64% and 51% of the variability of the yield spread, while the Consumer Sentiment index explains 23% of the variability.

Multiple regression analysis (MRA). When more than one independent variable is regressed against the dependent variable, they each may mediate the effect of the other. Multiple regression is a statistical process that controls for this. This process was employed to model the relationship between the independent variables and the dependent variable (yield spread). The analysis was run separately for each period because datapoints were different for the different independent variables - government institutional artifacts and most macroeconomic indicators are reported monthly, GDP is reported quarterly, and Fortune 500 company performance data is published annually. If they were run simultaneously, there would be too many missing values for several cases on different variables.

Multicollinearity and singularity. Multicollinearity and singularity can inflate the standard errors, thus making some variables statistically insignificant while they should be

otherwise significant. Multicollinearity and singularity usually surfaces when the independent variables (IVs) in a multiple regression model are very highly correlated (.90 or greater) and singularity is when the IVs are perfectly correlated and one IV is a combination of one or more of the other IVs. Convention dictates that if the pair-wise correlation between two regressors exceeds 0.8, multicollinearity may present an issue in the regression analysis.

Multicollinearity does not reduce the predictive power or reliability of the model as whole. According to Vaughan & Berry (2005), collinearity is problematic when the researcher's purpose is *explanation* rather than *prediction*. They contend that even though collinearity makes it more difficult to achieve significance of the collinear variables, if such estimates are statistically significant, they are as reliable as any other variables in a model. According to Becker (1983), "unlike simultaneity, multicollinearity does not result in biased least-squares coefficient estimators" (p. 8)

In order to check for multicollinearity and singularity among the independent variables, Pearson's correlation analysis was used. The results of the correlation are reported in Table 4.

The pairwise correlation exceeded .80 for the following regressors:

1. Manufacturers' New Orders Durables and Unemployment Rate
2. Manufacturers' New Orders Durables and Industrial Production
3. Manufacturers' New Orders Durables and Capacity Utilization
4. Manufacturers' New Orders Durables and Manufacturers' New Orders Capital Goods
5. Manufacturers' New Orders Capital Goods and Unemployment Rate
6. Manufacturers' New Orders Capital Goods and Industrial production
7. Manufacturers' New Orders Capital Goods and Capacity Utilization

To mitigate any potential validity concerns that may arise regarding individual predictors, one of the strategies recommended by Alheety and Gore (2009) is to choose one representative variable from each group. Accordingly, two independent variables were dropped from the analysis:

1. Manufacturers' New Orders Durables
2. Manufacturers' New Orders Capital Goods

Any adverse outcome from removing these two variables is moderated by the fact that other indexes in the list of macroeconomic variables take into account their impact on the economy. The Leading Economic Index (LEI), for example, is a composite index that is constructed by averaging out component indicators, such as Manufacturers New Orders. Likewise, the Industrial Production index is constituted from various measures which include the outputs from manufacturing industries. A detailed summary of the results of the Pearson's correlation exercise is provided in Table 12.

Table 12

Pearson's correlation matrix of independent variables (significant at $p < 0.01$ and $p < 0.05$)

	LEI	UR	IP	CU	ISMNOI	HS	PI	PO	CPI	PPI	CCI	MNO-D	MNO-CG	AMSR
LEI	1													
UR	0.147	1												
IP	-0.023	-0.438	1											
CU	-0.245	-0.114	-0.390	1										
ISM NOI	0.344	-0.088	0.142	0.070	1									
HS	0.271	-0.075	0.086	-0.050	0.442	1								
PI	0.152	0.216	-0.195	0.204	0.148	0.090	1							
PO	0.330	0.192	-0.195	0.183	0.063	0.098	0.362	1						
CPI	-0.332	0.379	-0.266	0.275	-0.273	-0.090	0.161	0.171	1					
PPI	0.128	0.187	-0.109	0.117	0.060	0.004	0.218	0.186	0.107	1				
CCI	0.003	-0.579	0.249	0.444	0.393	0.023	-0.097	-0.068	-0.329	-0.062	1			
MNO-D	-0.057	-0.904	0.900	0.838	-0.655	-0.182	0.035	-0.193	-0.346	0.040	0.502	1		
MNO-CG	-0.210	-0.956	0.951	0.879	-0.738	-0.251	0.006	-0.099	-0.211	0.034	0.570	0.938	1	
AMSR	-0.271	-0.969	0.976	0.926	-0.709	-0.198	0.097	-0.002	-0.145	-0.001	0.566	0.908	0.966	1
CSI	0.350	-0.531	0.493	-0.261	0.583	0.109	-0.255	-0.183	-0.602	-0.166	0.724	-0.574	-0.532	-0.561

The following key identifies the variable represented by each acronym in Table 12:

Acronym	Variable
LEI	Leading Economic Index
UR	Unemployment Rate
IP	Industrial Production
CU	Capacity Utilization
ISMNOI	Institute of Supply Management New Orders Index
HS	Housing Starts
PI	Personal Income Compounded Rate of Change
PO	Personal Outlays Compounded Rate of Change
CPI	Consumer Price Index Compounded Rate of Change
PPI	Consumer Price Index Compounded Rate of Change
CCI	Consumer Confidence Index
MNO-D	Manufacturers' New Orders Index Durable
MNO-CG	Manufacturers' New Orders Index Capital Goods
AMSR	Advanced Monthly Sales Retail
CSI	Consumer Sentiment Index

Tables 13, 14, 15, and 16 report the statistically significant results emerging from the multiple regression analysis (MRA):

Table 13

Statistically significant results of MRA: 1970-1972 (Dependent variable: yield spread)

Variable	<i>F</i> Value	Pr < <i>F</i>	Adj. <i>R</i> -Square	<i>T</i> Value
Industrial Production	9.43	<0.0001	0.4484	-5.29*
Capacity Utilization	9.43	<0.0001	0.4484	-6.43*

Note. * $p < 0.01$

Industrial Production and Capacity Utilization predict the yield spread within a 1% level of significance, suggesting that there is a less than 1% chance that these findings are not true. These levels of significance denote very strong evidence against the null hypothesis (H_0 : Independent variable does not predict the yield spread).

The p -value associated with the F -ratio is less than 0.0001, suggesting that the null hypothesis (H_0 : Model has no predictability) can be rejected. Therefore, the model reliably predicts the yield spread. The regression model explains 45% of the variability of the yield spread. Other econometric models that predict recessions tend to explain 30% or more of the variation in the measure of real activity (Estrella & Hardouvelis, 1991).

Table 14

Statistically significant results of MRA: 1978-1989 (Dependent variable: yield spread)

Variable	F Value	Pr < F	Adj. R-Square	T Value
Industrial Production	11.87	<0.0001	0.5795	-2.69*
Capacity Utilization	11.87	<0.0001	0.5795	-3.26*
Housing Starts	11.87	<0.0001	0.5795	-2.38**
Consumer Confidence Index	11.87	<0.0001	0.5795	-3.58*
Consumer Sentiment Index	11.87	<0.0001	0.5795	4.32*

Note. * $p < 0.01$, ** $p < 0.05$

Industrial Production, Capacity Utilization, Consumer Confidence Index, and Consumer Sentiment Index predict the yield spread within a 1% level of significance, suggesting that there is a less than 1% chance that these respective findings are not true. Housing Starts predicts the yield spread within a 5% level of significance, suggesting that there is a 5% chance that this finding is not true. These levels of significance offer very strong evidence against the null hypothesis (H_0 : Independent variable does not predict the yield spread).

The p-value associated with the F -ratio is less than 0.0001, suggesting that the null hypothesis (H_0 : Model has no predictability) can be rejected. Therefore, the model reliably predicts the yield spread. The model explains 58% of the variability of the yield spread. Other econometric models that predict recessions tend to explain 30% or more of the variation in the measure of real activity (Estrella & Hardouvelis, 1991).

The p -value associated with the F -ratio is less than 0.0001, suggesting that the null hypothesis (H_0 : Model has no predictability) can be rejected. Therefore, the model reliably predicts the yield spread. The model explains 70% of the variability of the yield spread.

Table 15

Statistically significant results of MRA: 2004-2006 (Dependent variable: yield spread)

Variable	F Value	$\text{Pr} < F$	Adj. R -Square	T Value
Housing Starts	37.71	<0.0001	0.9504	2.22**
Consumer Confidence Index	37.71	<0.0001	0.9504	-3.08*
Consumer Sentiment Index	37.71	<0.0001	0.9504	4.53*
Congressional Hearings	37.71	<0.0001	0.9504	2.50**

Note. * $p < 0.01$, ** $p < 0.05$

The Consumer Confidence Index and Consumer Sentiment Index predict the yield spread within a 0.01 level of significance, suggesting that there is less than one chance in 100 that these findings are not true. Housing Starts and Congressional Hearings predict the yield spread within a 0.05 level of significance, suggesting that there is are five chances in 100 that this finding is not true. These levels of significance offer very strong to moderate evidence against the null hypothesis (H_0 : Independent variable does not predict the yield spread).

The p -value associated with the F -ratio is less than 0.0001, suggesting that the null hypothesis (H_0 : Model has no predictability) can be rejected. Therefore, the model reliably predicts the yield spread. The model explains 95% of the variability of the yield spread.

Multiple regression analysis was not run for quarterly data because there was only one variable (GDP). No meaningful results were obtained when multiple regression analysis was run

on the annual data (company performance data), because there were insufficient observations.

The model returned four errors:

1. Model is not full rank.
2. Least squares solutions for the parameters are not unique.
3. Some statistics will be misleading.
4. The reported degrees of freedom (zero) means that the estimate is biased.

Table 16 provides a summary of the independent variables that have a statistically significant relationship with the yield spread, categorized by period:

Table 16

Summary of results of MRA for all four periods (Dependent variable: yield spread)

Variable	1970-1972	1978-1989	2004-2006
Industrial Production	✓	✓	
Capacity Utilization	✓	✓	
Housing Starts		✓	✓
ISM New Orders		✓	
CPI Compounded Rate of Change		✓	
Consumer Confidence Index		✓	✓
Consumer Sentiment index		✓	✓
Congressional Hearings			✓

Logistics regression model (Logit model). Logistics regression analysis (LRA) was run for separate periods because datapoints were different for the different independent variables - government institutional artifacts and most macroeconomic indicators are reported monthly, GDP is reported quarterly, and Fortune 500 company performance data is published annually. The results of the analysis are reported in Table 17, 18 and 19, and the following key outputs are distinguished (UCLA Academic Technology Services, 2010):

1. *Estimate*: These are the ordered logit regression coefficients. The conventional interpretation of this coefficient is that for a one unit increase in the predictor, the dependent variable level is expected to increase or decrease by its respective regression coefficient in the logit scale, while the other variables in the model are held constant. A positive regression coefficient signals that a one unit increase in the predictor variable results in the increased odds of a recession occurring ($P(Y=1)$), while a negative regression coefficient signals that a one unit increase in the predictor variable reduces the odds of a recession occurring.
2. *Wald-Chi Square and Pr > Chi Square*: The *Wald Chi Square* is used to test the statistical significance of each coefficient in the model. The *Pr > Chi Square* is the associated p-value that is taken into consideration in determining whether the test statistic is significant. For this analysis, the alpha level is set at 0.05. Thus, if the value for *Pr > Chi Square* is less than or equal to 0.05, the *Wald Chi Square* statistic is deemed to be statistically significant, and the parameter (e.g. Industrial Production) is considered to be a predictor variable.
3. *Point Estimate*: These are the proportional odds ratios. The interpretation of the point estimate for this analysis is that for a one unit change in the predictor variable, the

odds for a recession occurring ($P(Y=1)$) is increased, decreased or equal to 1- (point estimate).

Table 17

Statistically significant results of LRA: 1970-1972

Variable	<i>DF</i>	Estimate	Standard Error (Estimate)	Wald <i>Chi-Square</i>	Pr > <i>ChiSq</i>	Point Estimate
Industrial Production	1	0.1876	0.0825	5.1667	0.0230	1.206
Capacity Utilization	1	1.5743	0.5089	9.5691	0.0020	4.827
Consumer Confidence Index	1	-0.1051	0.0500	4.4214	0.0355	0.900

Note. Alpha level set at 0.05

The estimated probabilities are calculated by estimating the model for the period 1970 to 1972. For every one unit increase in Industrial Production, odds in favor of a recession ($P(Y=1)$) are estimated to be increased by a multiplicative factor of 1.2 (i.e., 1.2 times) or 21%, holding other variables constant. For every one unit increase in Capacity Utilization, the odds of a recession increases by a multiplicative factor of 4.82 (i.e., 4.82 times), holding other variables constant. The odds in favor of a recession decrease by 0.9 times or 10% when the Consumer Confidence Index increases by one unit, holding other variables constant.

Table 18

Significant results of LRA: 1978-1989

Variable	DF	Estimate	Standard Error (Estimate)	Wald Chi-Square	Pr > ChiSq	Point Estimate
Industrial Production	1	0.3101	0.1274	5.9215	0.0150	1.364
ISM New Orders	1	0.4732	0.1766	7.1813	0.0074	1.605
Consumer Confidence Index	1	0.4244	0.1655	6.5753	0.0103	1.529
Consumer Sentiment Index	1	-.06784	0.2047	10.9828	0.0009	0.507

Note. Alpha level set at 0.05

The estimated probabilities are calculated by estimating the model for the period 1978 to 1989. The odds in favor of a recession ($P(Y=1)$) increase by 1.36 times or 36% for every one unit of increase in the Industrial Production, holding other variables constant. For every one unit increase in the ISM New Orders Index, the odds in favor of a recession increase by 1.61 times or 61%, holding other variables constant. Finally, the odds of a recession increase by 1.53 times or 53% for every one unit of increase in the Consumer Confidence Index, holding other variables constant. The odds of a recession decrease by 0.51 times or 49% when the Consumer Sentiment Index increases by one unit, holding other variables constant.

Notes on missing tables.

1. There were no significant results for the period 2004-2006.
2. There is only one quarterly variable (GDP) and it was not significant.

3. There were not enough observations to run multiple logistic regressions of more than 1 variable on the Company Performance Data (because of insufficient degrees of freedom).

Individual testing of variables. Logistic regression was run individually on those variables that failed to emerge as predictor variables from the analysis previously conducted. Regression on company performance data yielded no statistically significant results. However, the logit model did yield statistically significant results for macroeconomic variables and government institutional artifacts. The results of the simple logistic regression are reported in Table 19.

Table 19

Statistically significant results of simple LRA on previously rejected variables

Variable	DF	Estimate	Standard Error (Estimate)	Wald Chi-Square	Pr > ChiSq	Point Estimate
Congressional Hearings	1	0.0549	0.0263	4.3698	0.0366	1.056
Manufacturers' New Orders Durables	1	0.00025	0.00012	4.7463	0.0294	1.000
CPI Compounded Rate of Change	1	2.8844	0.7244	15.8537	<0.0001	17.893
LEI Rate of Change	1	-0.3444	0.1745	3.8962	0.0484	0.709

Note. Alpha level set at 0.05

The odds of a recession ($P(Y=1)$) increase by 1.06 times or 6% for every one unit of increase in the number of congressional hearings held, holding other variables constant. For every one-unit increase in CPI Compounded Rate of Change, the odds of a recession increase by

17.89 times, holding other variables constant. The odds of a recession decrease by 0.71 times or 29% when the LEI increases by one unit, holding other variables constant.

Table 20

Summary of logistics regression analysis: 1970-2006

Variable	1970-1972	1978-1989	2004-2006	1970-2006
Industrial Production	✓	✓		
Capacity Utilization	✓			
ISM New Orders		✓		
CPI Compounded Rate of Change				
Consumer Confidence Index	✓	✓		
Consumer Sentiment index		✓		
LEI Rate of Change				✓
Manufacturers' New Orders Durables				✓
Congressional Hearings				✓

Summary of Results

Using the yield curve inversion as the signal for a recession, the regression analysis found that these macroeconomic indicators predicted the movement of the yield spread twelve months ahead: Industrial Production index, Capacity Utilization index, ISM New Orders index, CPI Compounded Rate of Change, Consumer Confidence index, Consumer Sentiment index, and the rate of change in the LEI. The analysis also found that these institutional artifacts predicted the movement of the yield spread twelve months ahead: Current Ratio and Total Debt to Assets ratio of Fortune 500 companies, and Congressional hearings on economic matters. The specific

measure of the yield curve employed for this study was based on the difference between interest rates on Treasury securities of ten years minus three months. The findings that relate to government information sources and corporate institutional artifacts are analyzed in the subsequent chapter. These findings are particularly important as they bring a unique perspective to the business cycle modeling process that has not been explored previously.

Chapter Five

Conclusions, Implications and Future Research

The previous chapter presented the findings from the simple, multiple and logistics regression modeling of macroeconomic indicators, government information sources and performance data of public companies. This chapter discusses these findings within the context of the research questions that guide this study, and draws conclusions accordingly. The implications of these findings and conclusions are then considered, and suggestions for future research are provided.

Over the last few decades several empirical studies have examined the role of macroeconomic indicators in predicting the future macroeconomic environment, and a large number of these studies have specifically focused on recessions. Consequently, a substantial body of research currently exists which postures a variety of macroeconomic indicators as predictive agents with varying degree of predictive powers and forecasting abilities. Despite the vast quantity of research and information presently available in this area accurate forecasting of recessions continues to be elusive. As a result of this, businesses and society are generally unprepared when a recession strikes, thereby worsening its impact.

This study investigated the current state of macroeconomic forecasting, identified potential gaps in the manner it is presently conducted, and addressed these gaps by introducing and modeling new predictor variables that were not previously included in recession forecasting models. The variables introduced were institutional artifacts comprising of congressional

hearings data and presidential executive orders relating to economic matters, and Fortune 500 company performance data. The inclusion of public policy dialogue and corporate performance data as predictor variables in recession forecasting models not only extends the information paradigm associated with recession forecasting, but it also designates the unique contribution that this study makes to this area of research. To obtain a valid estimation of the predictive power of institutional artifacts, and to avoid falsely inflating their significance, the new variables were not modeled in isolation. Macroeconomic indicators published by government agencies and private institutions were retained as variables in the respective regression models used in this study.

Summary of Findings and Conclusions

The study found that the current ratio and total debt to assets ratio of Fortune 500 companies, and congressional hearings on economic matters significantly predicted the movement of the yield spread twelve months ahead. The yield curve inversion was used as the signal for a recession. Since 1960, a yield curve inversion has preceded every recession on record. The specific measure of the yield curve employed for this study was based on the difference between interest rates on Treasury securities of contrasting maturities, namely, ten years minus three months, which provided a reasonable combination of accuracy and robustness over long time periods (Moench, 2008). The literature review provides supportive empirical evidence of the yield spread as a leading predictor of economic recessions.

Simple regression analysis was first used to model the relationships between the dependent variable (the yield spread) and the independent variables to assess which variables predicted the yield spread. Thereafter, to control for the mediating effect of one independent variable on another, multiple regression analysis was employed. The statistically significant

predictor variables emerging from the multiple regression analysis served as parameters for the logistic regression model. Table 21 summarizes the output from all three regression models, identifying the statistically significant predictor variables and the level of significance associated with each variable:

Table 21

Consolidated Table of Results

Predictor Variables	Simple Regression		Multiple Regression						Logistics Regression					
	1970-2006		1970-1972		1978-1989		2004-2006		1970-1972		1978-1989		1970-06	
	Sig.	Pr.	Sig.	Pr.	Sig.	Pr.	Sig.	Pr.	Sig.	Pr.	Sig.	Pr.	Sig.	Pr.
LEI*	✓	0.01											✓	0.04
Industrial Production			✓	0.01	✓	0.01			✓	0.02	✓	0.01		
Capacity Utilization	✓	0.01	✓	0.01	✓	0.01			✓	0.00				
ISM New Orders*	✓	0.01											✓	0.01
Housing Starts	✓	0.05			✓	0.05	✓	0.05						
CPI (Compounded Rate of Chg)	✓	0.01											✓	0.00
Consumer Confidence Index					✓	0.01	✓	0.01	✓	0.02	✓	0.01		
Mnfr. New Orders Durables	✓	0.01											✓	0.02
Mnfr. New Orders Capital Goods	✓	0.01												
Adv. Monthly Sales Retail	✓	0.01												
Consumer Sentiment Index	✓	0.01			✓	0.01	✓	0.01			✓	0.00		
Current Ratio	✓	0.05												
Market to Book	✓	0.10												
Total Debt to Assets	✓	0.05												
Congressional Hearings							✓	0.05					✓	0.03

Note. 1. LEI Rate of Change used for Logistics Regression Analysis (1970-2006)

Study findings relative to the major research questions. To determine whether the inclusion of institutional artifacts strengthened the predictive power of conventional forecasting models, this study was guided by two research questions:

1. Is there evidence of a predictive relationship between institutional artifacts and macroeconomic vulnerability?
2. Does the relationship between institutional artifacts and macroeconomic vulnerability provide any predictor variables that may serve as a long-range signaling device for a recession?

Is there evidence of a predictive relationship between institutional artifacts and macroeconomic vulnerability? The predictor variables emerging from simple regression analysis were all significant at conventional levels. Of the twelve predictor variables that emerged from the simple regression analysis, nine were macroeconomic indicators. This result was consistent with the status quo as far as econometric modeling was concerned – that is, current econometric models primarily employ macroeconomic indicators to make predictions about the economy.

After the multiple regression analysis was run, six variables surfaced as statistically significant, which is exactly half the number of predictor variables that came up as significant in the simple regression model. This was not surprising because an independent variable that is a significant predictor of a dependent variable in simple regression analysis may not necessarily be significant in multiple regression analysis, when all the independent variables are added into the equation. This happens because the variance that an independent variable shares with the dependent variable may overlap with the variance that is shared between another independent variable and the dependent variable. As a result of this, the first independent variable is no longer

uniquely predictive and thus would not show up as being significant in the multiple regression analysis.

When the logit model was run, using the six variables produced in the multiple regression model, four variables emerged as statistically significant. All four of them were macroeconomic variables. The logit model was then modified to run the remaining variables that comprise the dataset for this study. Each variable was modeled individually. Through this analysis, five additional variables emerged as useful predictors.

One third of the total number of company performance variables included in the simple regression model emerged as significant predictors of the yield spread twelve months into the future. The Current Ratio and Total Debt to Assets ratio were both significant at the five percent level, and the Market to Book ratio was significant at the ten percent level. Government institutional artifacts, on the other hand, were distinctly absent from the list of significant variables, i.e., simple regression analysis did not detect any significant association between the yield spread and congressional hearings or presidential executive orders.

For the 2004-2006 period multiple regression analysis yielded one institutional artifact, congressional hearings, as a significant predictor variable. The model explained 95% of the variance in the yield spread ($p < 0.0001$). Congressional hearings, again, emerged as a significant predictor variable, with a p -value of 0.03, when the logit model was run with single variables. The logit model failed to yield any significant predictor variables from company performance data.

Company performance data. The multiple regression model failed to run for company performance data because there were not enough degrees of freedom to obtain any significant or valid information, or simply, the number of observations for company performance data were not

large enough. Fortune 500 company performance data is only reported annually, unlike government institutional data, which is published monthly. With only three years in each analysis period, and only four analysis periods, the sample of observations were, ultimately, very few. A similar diagnosis may be tenable for why the logit model failed to yield any significant predictor variables from the company performance dataset. The data used for this specification contained too few observations to reliably estimate Fortune 500 company performance and its interaction with the yield spread.

The simple regression model, however, yielded three significant predictor variables. The Current Ratio and Total Debts to Assets explained sixty percent and fifty one percent of the variability of the yield spread, respectively, while the Market to Book ratio explained twenty two percent of the yield spread's variance. For context, it must be noted that other econometric models that predict recessions tend to explain thirty percent or more of the variation in the measure of real activity (Estrella and Hardouvelis, 1991). With this context in mind, The *R*-square values for the simple regression models analyzing current ratio and total debt to assets indicated that these models fit the data moderately well. The *R*-square value for the linear regression model analyzing the Market to Book ratio indicated that the model marginally fits the data, which was borne out by the explanation of the variance of the yield spread which is below the conventional average for predictive economic models.

Now to the question of whether there is evidence of a predictive relationship between Fortune 500 company performance data and macroeconomic vulnerability? According to the results of the simple regression analysis, the answer would be "yes." Current Ratios and Total Debt to Assets ratios offer more useful value than Market to Book ratios. It is possible that a larger dataset may have changed the results of this analysis. A larger dataset would have allowed

the multiple regression model to run, which, after controlling for the mediating effect of other variables, may have produced a different outcome. A larger dataset may have conceivably altered the outcome of the logit model with regard to Fortune 500 company performance ratios.

Government informational sources. Presidential executive orders failed to materialize as a significant variable in any of the regression models tested. As highlighted earlier, congressional hearings emerged as a significant variable in both the multiple regression model and the logit model. The multiple regression model for the 2004-2006 analysis period furnished convincing statistical significance for the tenability of congressional hearings as a significant predictor variable. The p -value associated with the F -ratio for this model was less than 0.0001, suggesting that the model reliably predicted the yield spread. Additionally, the multiple regression model explained ninety five percent of the variability of the yield spread, which significantly exceeds the conventional norm (thirty percent) of other econometric models that predict recessions. According to Pampel (2000), if $p < 0.05$ in the logit model, the variable contributes significantly to the prediction of the outcome variable. The p -value for congressional hearings was 0.03, confirming that this variable contributed significantly to the prediction of a recession.

Is there evidence of a predictive relationship between government institutional artifacts and macroeconomic vulnerability? According to the results of all three regression models, presidential executive orders do not share a predictive relationship with macroeconomic vulnerability. According to the results of the multiple regression analysis and the logistics regression analysis, there is statistical evidence that congressional hearings are a significant predictor of macroeconomic vulnerability.

To summarize this section within the context of the research question it addresses, the regression models employed in the analysis confirm that there is indeed evidence of a predictive

relationship between institutional artifacts and macroeconomic vulnerability. These artifacts are, however, restricted to congressional hearings data, and Fortune 500 companies' liquidity and financial leverage ratios, which specifically include the Current Ratio and Total Debt to Assets ratio.

Does the relationship between institutional artifacts and macroeconomic vulnerability provide any predictor variables that may serve as a long-range signaling device for a recession? The relationship between institutional artifacts and macroeconomic vulnerability produced three statistically significant predictor variables that serve as signaling devices for an approaching recession. In no specific order, these are:

1. Current Ratio (Rate of Change)
2. Total Debt to Assets Ratio (Rate of Change)
3. Congressional hearings

The findings suggest that a Fortune 500 company's liquidity and financial leverage affects not only the company fundamentals, but brings to bear heavily on the economy as whole. The current ratio and total debt to assets ratio were computed from performance data of a sample of twenty Fortune 500 companies that consistently appeared on the Fortune 500 list for every year analyzed in this study.

Current ratio. The current ratio is one of the measures of a company's liquidity. Liquidity ratios assess the ability of a firm to pay its bills on time. It also relates to how quickly and easily a firm can convert its non-cash assets, like accounts receivable or inventories, into cash (Salehi, 2009). Because of its critical importance to the corporation, corporate executives devote much attention to the management of corporate liquidity (Kallberg , 1992, Dittmar, 2002). The finding that the current ratio (rate of change) is a significant predictor of the yield spread is highly

tenable. This was borne out in a recent study which found that liquidity of non-financial companies had fallen by \$250 billion in the second half of 2007, going from \$5.5 trillion to \$5.25 trillion (Johnston, 2008). Given that the Great Recession officially started in December 2007, this decline in corporate liquidity clearly preceded it. Given the magnitude of the drop in liquidity, it is highly unlikely that the decline occurred in just a few months. This points to the possibility that the onset of the decline in corporate liquidity potentially started at least a year before, thus making the finding that the current ratio is a predictor variable very defensible.

Total debt to assets. The total debt to assets ratio is one of the measures of a corporation's financial leverage. Leverage refers to the degree to which the corporation is using borrowed money, or a measurement of how much the corporation is using borrowings compared to its total assets. A corporation is deemed to be highly leveraged when it has taken on a disproportionate amount of debt. Knowledge of a corporation's leverage helps the providers of long-term funds to assess the degree of protection they have if they have loaned, or are contemplating loaning money to the corporation. A highly leveraged corporation is very susceptible to bankruptcy.

The tenability of total debt to assets as a predictor of recessions is probably best borne out in the events characterizing this last recession. Between 2004 and 2007 the leverage ratios of the largest five financial corporations in the United States started increasing dramatically. By the time the recession was officially declared as such by the National Bureau of Economic Research, these five institutions reported over \$4.1 trillion in debt, which was about thirty percent of U.S. nominal GDP for 2007 (Molla, 2010). One of the five corporations in question, Bear Stearns, saw its leverage ratio rise to 33:1 in that period. This means that for every dollar in equity, it held 33\$ of debt. The leverage ratios at the other firms also showed similar sharp increases, and the prevailing sentiment among economists was that these financial corporations were over-

leveraged (Labaton, 2008). The onset of the sharp increase in the leverage ratio of these corporations mirrors the time period postulated in this study as the predictive window for an oncoming recession. This industry example provided supporting evidence for the robustness and validity of this finding.

Congressional hearings. Given the uniqueness of this finding from an economic modeling perspective, questions about its pervasiveness across time are bound to ensue. A detailed analysis of each year's data showed that, relative to the other major topics of discussion or subject categories, hearings relating to economic matters featured prominently in every congressional session in the three years preceding each recession examined in this study (see Figures 1 to 12).

Between 1978 and 1980 the economy was the most dominant topic of discussion in congressional committee hearings. By 1980, the number of hearings relating to the economy significantly superseded every other government matter, suggesting that in the year preceding the recession of 1981, Congress must have had reason to believe that a major recession was looming. A similar pattern surfaced in the period between 1987 and 1989. Economic-related issues were the preeminent topic of discussion in congressional hearings, peaking as early as 1987 which was about three years before the recession of 1990. Once again, the likelihood of some foreknowledge of troubling elements in the economy is plausible. Finally, between 2004 and 2006, even though economic-related issues did not dominate congressional hearings, there was a distinct increasing trend in the number of hearings conducted on this subject in that period (see Figure 13). A reasonable hypothesis about this increasing trend is that it was initiated by speculations of approaching macroeconomic instability or business cycle contraction.

Proponents of the view that congressional activity is intrinsically reactive may legitimately contend that if congressional policy-making activity (pertaining to the economy) was indeed predictive, then why, historically, was the public not made aware of impending peril? And next, how does one reconcile the ever-optimistic economic outlook consistently communicated ahead of recessions by this very establishment that purportedly has insight that suggests information to the contrary? The political science and rhetorical theory literature provide some insight into answering these questions.

The first plausible explanation for this phenomenon lies with political posturing and grandstanding. Political posturing refers to the propensity to take a route that is politically advantageous, and grandstanding refers to behaving in manner to please or impress constituents. Congress has the difficult task of having to balance local interests with national needs, the rhetorical force of their communications, and their relationship with the public, which determines reelection prospects. Thus, the conflicting demands of policymaking and representation sometimes impacts information veracity (Ostrom & Ostrom, 1971). A study conducted by Mucciaroni and Quirk (2006) found that members of Congress come forward with the whole truth only about a quarter of the time, not because of a pathological propensity to lie, but because they have to make strategic compromises. When unfavorable economic news is disseminated, the public typically reacts by blaming Congress for the adverse economic conditions being reported, thereby threatening reelection prospects. In the face of such threats, a politically expedient route is often contemplated with regard to information dissemination.

Another probable explanation of this phenomenon is the establishment's proclivity to defer to the self-fulfilling-prophecy hypothesis. This hypothesis suggests that communication of unfavorable economic news will cause the public to panic and react irrationally, thereby, further

fuelling the unfavorable climate and guaranteeing that the worst case scenario materializes. It is obvious why a vicious cycle like this will exacerbate an already bad situation in the economy.

Ultimately, the strategic imperative driving Congress's approach to communication is to maintain order and defuse resistance to the established political system. So how does one reconcile this study's finding that congressional hearings offer predictive signals of economic contraction, with the conflicting narratives and rhetoric that have historically been conveyed by Congress to the public? *By shifting the information paradigm currently characterizing this process.* What this means is that instead of using the information and rhetoric publicly communicated by Congress via the media as the barometer to assess the state of the economy, access the primary source documents which provide an accurate, unbiased, authoritative record of congressional proceedings, and use this as the basis to determine the future outlook.

Figure 9. Relative prominence of economic-related issues in congressional hearings in 1970

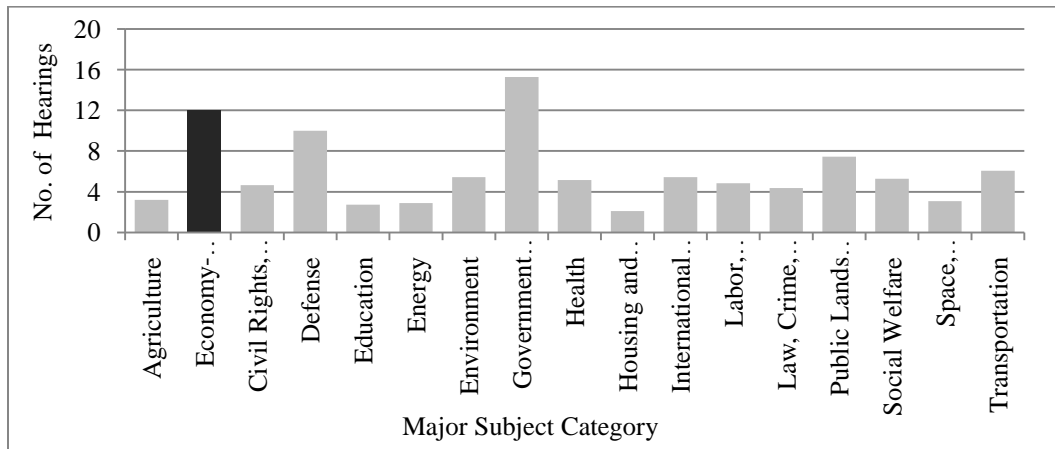


Figure 10. Relative prominence of economic-related issues in congressional hearings in 1971

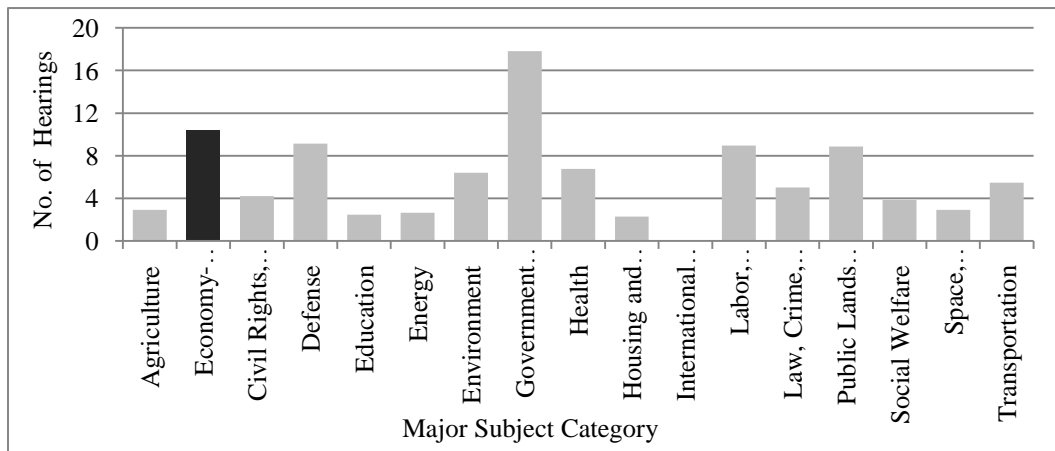


Figure 11. Relative prominence of economic-related issues in congressional hearings in 1972

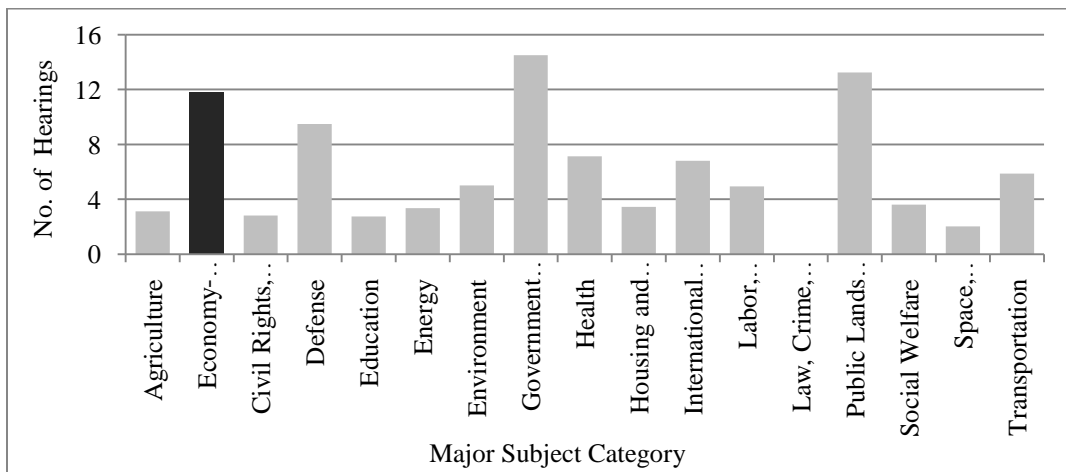


Figure 12. Relative prominence of economic-related issues in congressional hearings in 1978

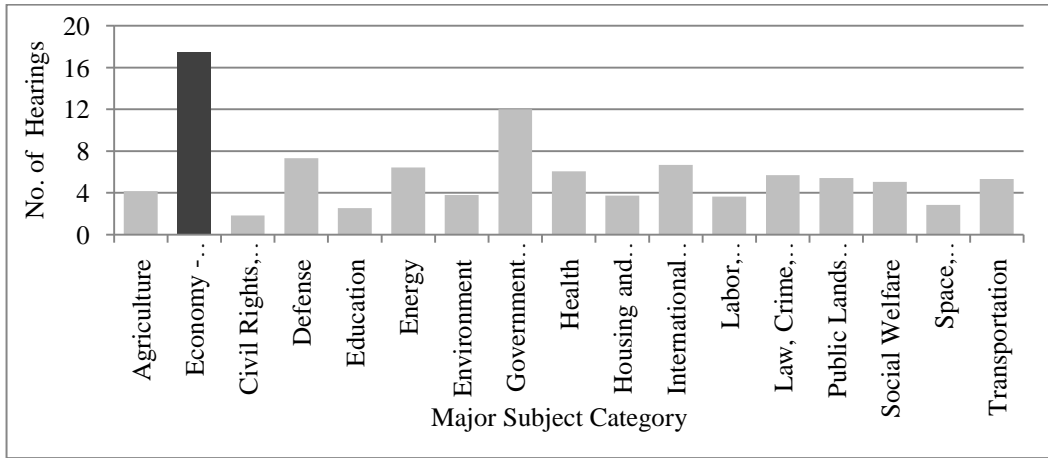


Figure 13. Relative prominence of economic-related issues in congressional hearings in 1979

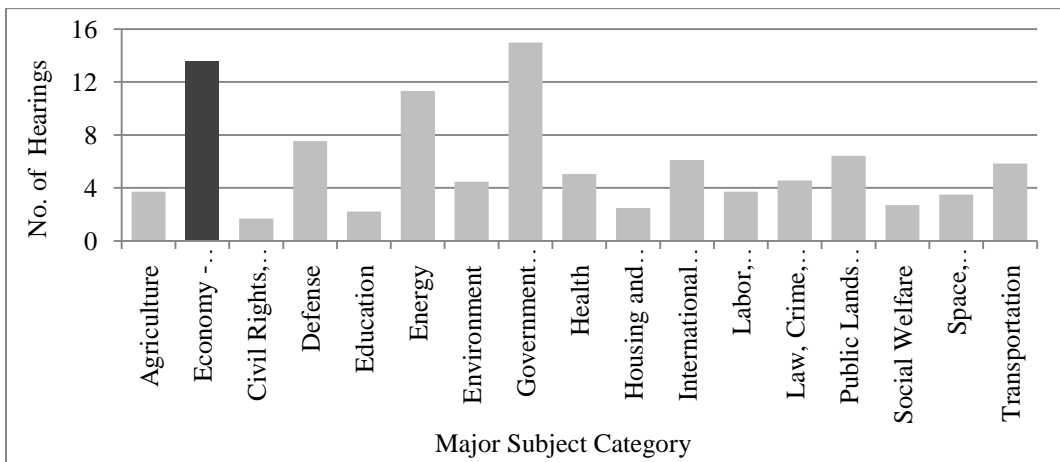


Figure 14. Relative prominence of economic-related issues in congressional hearings in 1980

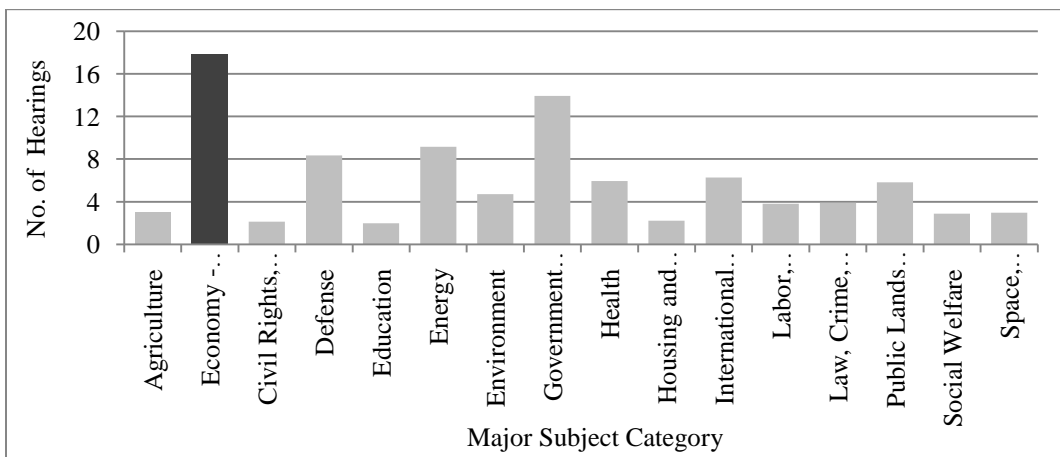


Figure 15. Relative prominence of economic-related issues in congressional hearings in 1987

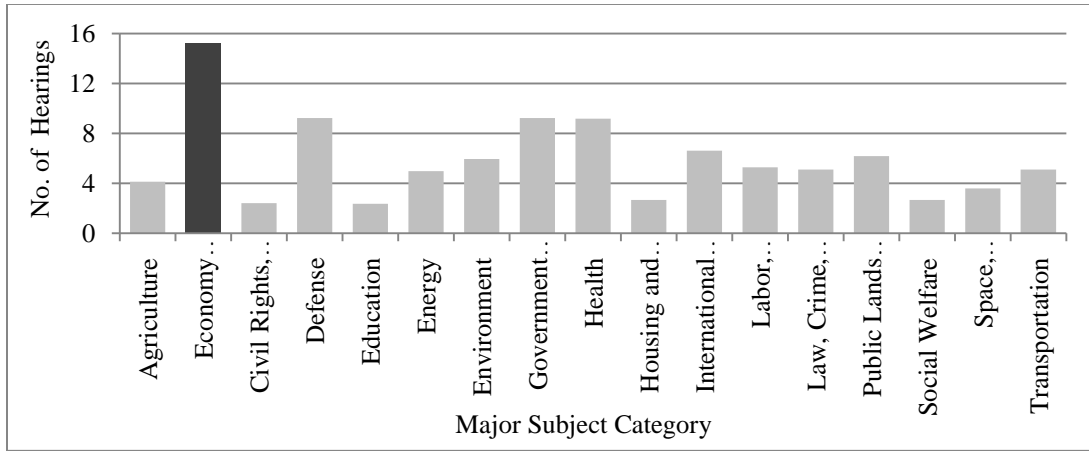


Figure 16. Relative prominence of economic-related issues in congressional hearings in 1988

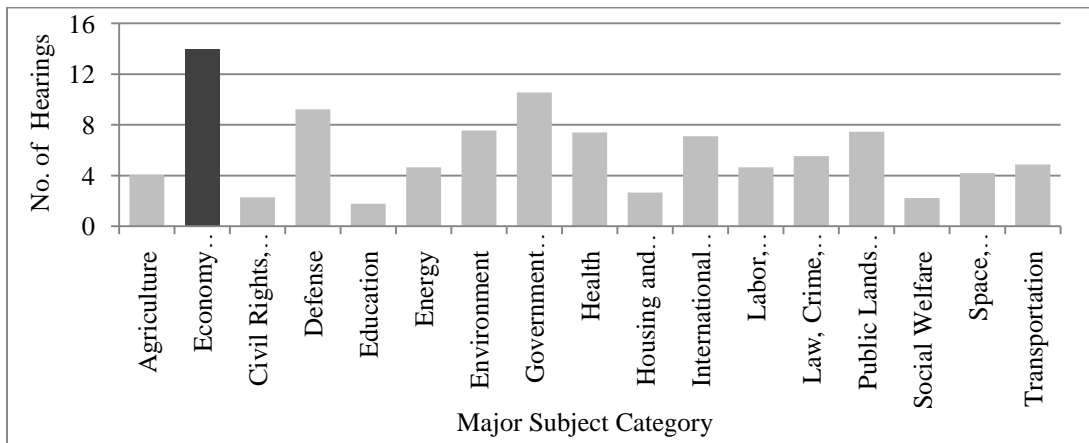


Figure 17. Relative prominence of economic-related issues in congressional hearings in 1989

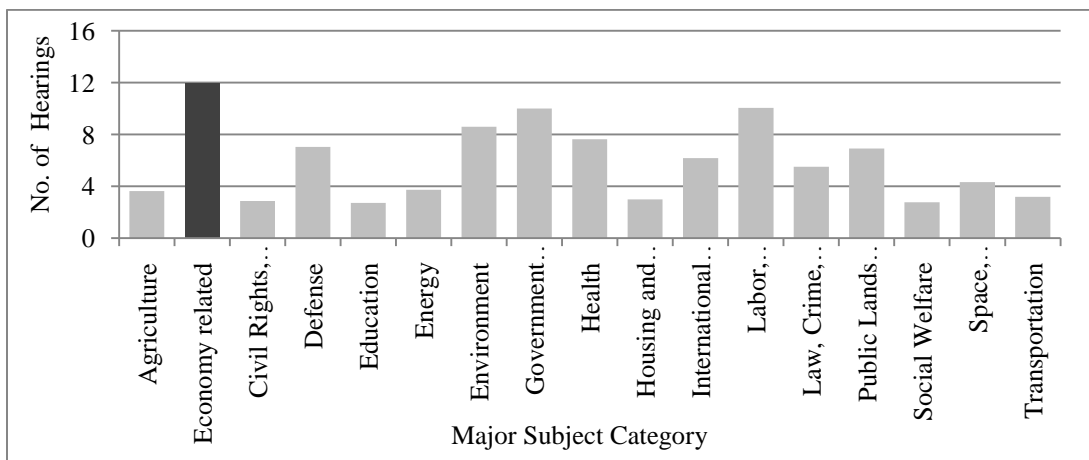


Figure 18. Relative prominence of economic-related issues in congressional hearings in 2004

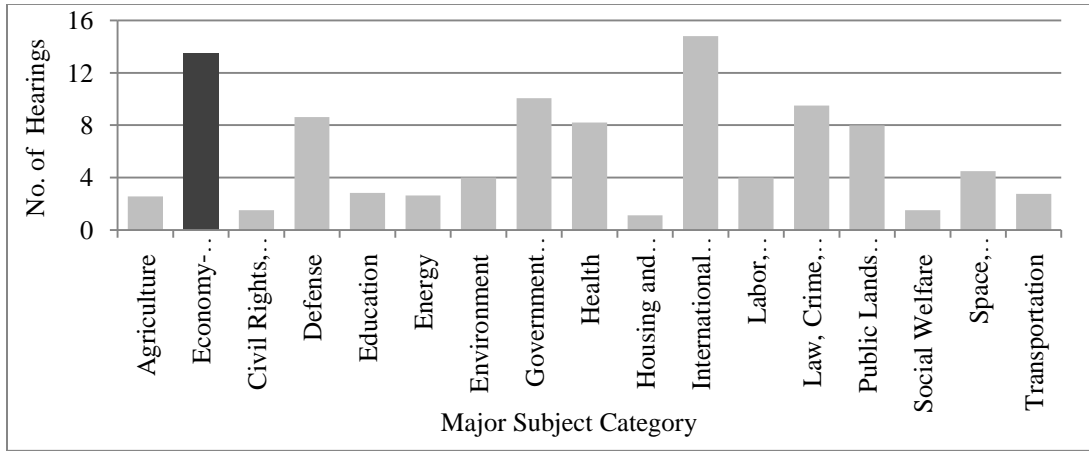


Figure 19. Relative prominence of economic-related issues in congressional hearings in 2005

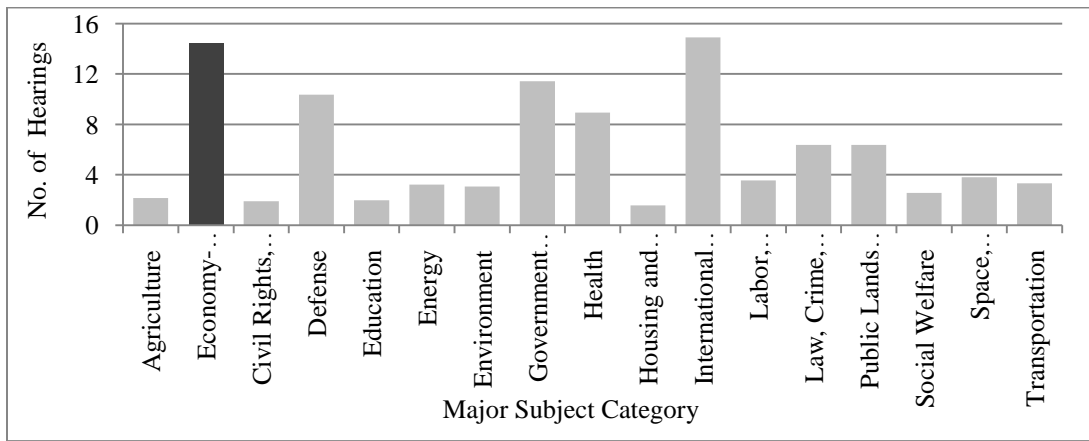


Figure 20. Relative prominence of economic-related issues in congressional hearings in 2006

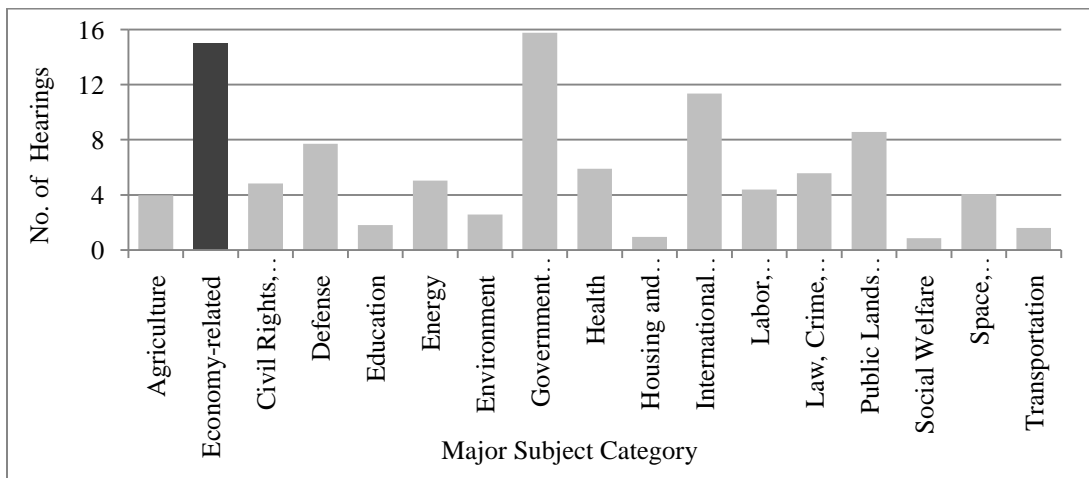
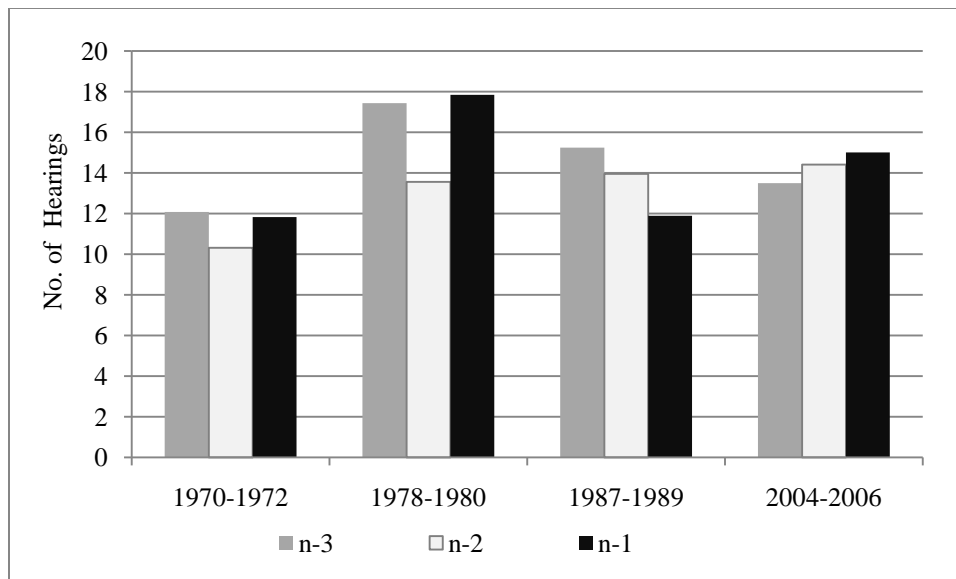


Figure 21. Trend in congressional hearings on economic matters (n=year of recession)



Implications of Findings

Based on a review of the literature, the following institutional artifacts were identified as possible predictors of a recession in the United States:

- Congressional Hearings relating to economic issues
- Presidential Executive Orders relating to economic issues
- The financial ratios of Fortune 500 Companies. These ratios specifically included:
 - Current Ratio
 - Total Asset Turnover
 - Total Debts to Assets
 - Times Interest Earned
 - Profit Margin on Sales
 - Return on Assets
 - Return on Equity
 - Price / Earnings

- Market / Book

The findings of the study rejected 73% of the possible predictor variables, and established the following three variables as having varying degrees of predictive power:

1. Current Ratio
2. Total Debt to Assets
3. Congressional Hearings relating to economic issues

The implicit suggestion in the literature that all financial ratios have strong predictive power was not borne out in this study. More than three-fourths of the Fortune 500 company financial ratios identified as possible predictor variables were rejected. As highlighted in chapter two, Lewellen (2004) and Park (2010) specifically identified the Price / Earnings ratio and the Book to Market ratio as having solid predictive power. In addition, Riahi-Belkaoui (1998) posited that the use of financial ratios in multivariate-based models in financial analysis can *predict* and explain important economic events. The magnitude of the proportion of variables rejected in this study, however, challenges these categorical assertions. Moreover, it brings into question the commonly-held precept that the performance of Fortune 500 companies is a barometer of economic activity (Hasan, 2008).

The results of the study, however, do not entirely refute the notion that the performance data of Fortune 500 companies are good tools for predicting economic contractions. It vindicates the assertion to the extent that it is made with specific qualifications that emphasize the discriminating powers of prediction of the different categories of financial ratios. To this end, it is more accurate to suggest that the liquidity and financial leverage ratios of Fortune 500 companies provide predictive insight into the business cycle. Other financial ratios may be employed to obtain predictive insights into whether a company's financial health is improving or

deteriorating over time, and are useful for undertakings such as the probabilistic predictions of bankruptcies (Ohlson, 1980; Beaver, 1966; Altman, 1968), takeovers and corporate bond ratings (Riahi-Belkaoui, 1998).

The emergence of congressional hearings as a predictor variable, with the simultaneous rejection of presidential executive orders as a predictor, was a significant and unique finding. The finding was unique in that it redefines the process relating to the predictive modeling of recessions. Forecasting of the business cycle is inherently the domain of economists or economic analysts. It is not surprising, then, that conventional predictive models limit input variables to macroeconomic indicators. Employment of variables falling outside this classification is generally atypical. Even less common is the prospect of employing public policy dialogue. The literature provides fervid support in justification of this practice - researchers and analysts argue that Congress does not adopt a pro-active or visionary approach to policymaking, but rather, one that is reactive and legalistic. According to Smith, et al (2006), Congress is not equipped to execute rapid, coordinated efforts, which is a pre-requisite for efficient pro-active governing and policymaking. They concluded that congressional activity is slow, divided, and locked in *reactive* posture while lurching from event to event with no capacity to implement visionary executive action. These attributes ostensibly make congressional hearings a poor candidate for predictive modeling.

The results of the study strongly rejected this ideology, positioning congressional Hearing as a predictive and pre-emptive variable. Despite its uniqueness to the practice of economic modeling, the predictive power of congressional hearings does find support in the literature. Zelizer, et al (2004) argued that Congress is not a solely reactive institution and is extraordinarily sensitive to what is going on in the environment, which allows them to respond proactively.

Labonte and Makinen (2008), in support of this view, asserted that the cyclical behavior of the economy is of great interest to Congress for two reasons: it affects the position of the federal budget, which is a key indicator of how tax payer dollars are being spent and, cyclical contractions could potentially be remediated by well-timed policy changes. Evidence of this, they argued, included Congress's contemplation of a fiscal stimulus package to forestall a recession well *before* this last recession was officially declared a recession.

The concurrent emergence of congressional hearings as a predictor variable and rejection of presidential executive orders as a predictor variable is a significant finding because it is incongruent with the literature examining the nature of presidential and congressional rhetoric. The dissonance relates to the relationship between the two separate government entities that originate the respective rhetorical artifacts that constitute the variables in this study. While the literature posited that both congressional hearings and presidential executive orders were possible predictors of the business cycle, presidential rhetoric was distinctly ensconced as the driver of congressional rhetoric. The findings in the study refute this relationship between the variables that is established in the literature.

According to the political science research literature, a large number of studies have found that public bureaucracies respond to catalysts that materialize in the policy environment. One such policy environment stimulus that sets the agenda for congressional discourse is the presidential agenda. Moe (1982) postulated that independent regulatory commissions were not really independent of presidential direction and control. Chubb (1985) corroborated this assertion in a study that found that "political effects can be disaggregated into ideological and constituency-oriented demands made by the White House" (p. 994). Eshbaugh-Soha & Peake (2004) determined that, "Theoretically speaking, the president may have influence over others'

attention to policy issues because the president is the central figure in American politics” (p. 166). The Presidential agenda evidently defines what the looming or extant problems in the relevant social, political, or economic environment are, and dictates the high-priority items affecting the nation. Congress then sets its agenda for discourse, ostensibly taking its cue from presidential rhetoric. Thus, if the presidential policy agenda has a distinct economic focus, for example, this will result in congressional committee agendas being increasingly concentrated around economic issues.

If this were indeed the case, presidential executive orders would have also emerged as a significant predictor variable, along with congressional hearings. This deduction is based on the transitive property of equality, which posits that if an element has a particular relationship to a second element which in turn has the same relationship to a third element, the first has this same relationship to the third element. While the findings refute the notion of presidential rhetoric driving congressional rhetoric, the study does not provide any evidence to refute the suggestion that the president is the central figure in American politics or that the president influences policy-issues. The study does, however, provide support for the argument that:

1. Congressional rhetoric is not entirely under the influence of the president, as is widely claimed in the literature, and
2. Congressional rhetoric is predictive and pre-emptive, while presidential rhetoric is not.

The fact that presidential executive orders are not predictive indicators indicates a remarkable degree of incongruence with the research paradigm positioning presidential rhetoric as an instrument of executive power that is driven by the rhetorical context. As highlighted in chapter two, the body of research in this field asserts that the rhetorical context is a function of

environmental forces (e.g., sociological, psychological, economic, etc) confronting the president at any given moment in time. Wood's (2007) study, for example, found that presidential rhetoric responded systematically to what the public perceived as being important issues. As the public's sensitivity to unemployment, inflation, the deficit, and other general economic issues increased, it was accompanied by a parallel increase in the intensity of presidential rhetoric on those issues. Therefore, in the period leading up to a recession the rhetorical context would, presumably, be dominated by economic forces. Following the order of the premise, these forces would then shift presidential priorities towards economic issues. Accordingly, presidential rhetoric would then be focused on placing economic issues on the public's agenda, and mobilizing them into action.

These assertions are not borne out by the results obtained in this study, bringing into question the widely accepted principle that the rhetorical context drives the presidential agenda. If Presidential rhetoric responded systematically to what the public perceived as being important issues, as claimed in Wood's (2007) study, then this response is likely to be primarily reactionary or ex post. Similarly, if presidential executive orders are, in fact, used to shape the institutional and political context over which presidents preside (Mayer, 2010), this shaping is likely of a more reactive, rather than generative, nature.

The apparent discordance between some of the findings of this study and the literature provides a unique contribution to the current knowledge base regarding institutional artifacts and the role they play in the prediction of recessions. The findings posture liquidity and financial leverage ratios as having more predictive power than the other families of financial ratios. The findings also clarify, through contradiction of the current literature, the relationship between presidential rhetoric and congressional rhetoric, and how these rhetorical artifacts shape public policy dialogue.

Avenues for Future Research

The outcomes emerging from this study provide a natural guide to future avenues for research. These outcomes mainly relate to findings extraneous to the scope of this dissertation.

The first avenue for further research relates to the finding that presidential executive orders are not predictive indicators. Given that this finding conflicts with the extensive body of research that postures presidential rhetoric as an instrument of executive power that is galvanized by the rhetorical context, it warrants further investigation into the nature of presidential rhetoric. Future studies should revisit the claims that the rhetorical context drives presidential agenda, and assess to what extent this is tenable. Additionally, these studies should investigate whether presidential executive orders are, in fact, used to shape the institutional and political context over which presidents preside (Mayer, 2010), and whether this shaping is of a more reactive, rather than generative, nature.

The second avenue for further research is also within the purview of rhetorical criticism and rhetorical theory. This study postulated that political posturing and grandstanding, and the self-fulfilling-prophecy hypothesis provided a plausible explanation for the conflicting information provided to the public, specifically when it related to a weakening economy. An analysis of the rhetorical artifacts that are initiated by Congress as public statements about the economy will provide useful insight into the contexts and exigences to which these artifacts are responding.

The third avenue for research relates to the macroeconomic variables that emerged as predictor variables. While macroeconomic variables such as industrial production and capacity utilization are acknowledged in the literature as venerable predictor variables, other variables like the consumer sentiment index and consumer confidence index were interesting findings.

Further investigation into the nature of these indicators as information artifacts will provide a deeper understanding of their specific informational characteristics which posture them as effective predictive agents. According to Moench (2008), the expectations hypothesis is one of the most pervasive theories of the determinants of the yield curve. However, this hypothesis has been repeatedly rejected in econometric tests. The consumer sentiment index and consumer confidence index both derive from consumer expectations about the economy. Further study of these artifacts will validate or refute this hypothesis, thereby contributing to the body of literature in this area.

The failure of Fortune 500 company performance data to yield significant variables in the multiple regression and logistics regression models was attributable to the fact that there were insufficient observations. A future study with an expanded dataset may strengthen the model and yield significant variables. Instead of limiting the period of analysis to three years before each recession, and limiting the entire study to four specific recessionary periods, future studies should model the financial performance data of the sample of Fortune 500 companies for the entire four-decade period.

Finally, future studies exploring whether industry factors strengthen the predictive power of variables will offer additional insight into predictive economic modeling. This study sampled twenty Fortune 500 companies that represented a broad range of industry sectors. However, industry effects were not examined. The possibility exists that the economy might be more sensitive to fluctuations and volatility within certain industry sectors. The identification of these industry sectors will strengthen the predictive power of the variables that have been identified as significant predictor variables in this study.

References

- Akerlof, G., & Shiller, R. (2009). *Animal spirits: How human psychology drives the economy, and why it matters for global capitalism*. New Jersey: Princeton University Press.
- Alheety, M. I., & S.D. Gore, S. D. (2009). Two strategies for removing multicollinearity. *International Journal of Statistics & Economics*, 3(A09), 62-79.
- Altman, E. I. (1968). Financial ratios, discriminant analysis and the prediction of corporate bankruptcy. *The Journal of Finance*, 23(4), 589-609. Retrieved from <http://www.jstor.org/stable/2978933>.
- Amihud, Y., & Mendelson, H. (1991). Liquidity, maturity, and the yields on U.S. treasury securities. *The Journal of Finance*, 46(4), 1411-1425. Retrieved from <http://www.jstor.org/stable/2328864>.
- Anderson, S., & Cavanagh, J. (2000). Report on the top 200 companies. Institute for Policy Studies. *Corporate Accountability Project*. Retrieved from <http://www.corporations.org/system/top100.html>.
- Bade, R., & Parkin, M. (2001). *Foundations of macroeconomics*. Boston, MA: Addison Wesley.
- Banks, J. S., & Weingast, B. R. (1992). The political control of bureaucracies under asymmetric information. *American Journal of Political Science*, 36(2), 509-524. Retrieved from <http://www.jstor.org/stable/2111488>.
- Barro, R.J. (2009, March 4). What are the odds of a recession? The Wall Street Journal. Retrieved from <http://online.wsj.com/article/SB123612575524423967.html>.
- Barro, R. J., Kamphuis, R. W., Kormendi, R. C., & Watson, J. W. H. (1989). *Black Monday and the future of financial markets*. Homewood, Ill.; Chicago, Ill.: Dow Jones-Irwin ; Mid America Institute for Public Policy Research.
- Bartels, L. (1997). Econometrics and presidential elections. *Journal of Economic Perspectives*, 11(3), 195-196.
- Baumgartner, F. R., Jones, B., & Larsen-Price, H. A. (1998). Lessons from the trenches: Quality, reliability, and usability in a new data source. *The Political Methodologist*, 8(2), 1-11.

- Baumgartner, F. R., Larsen-Price, H. A., Leech, B. L., & Rutledge, P. (in press). Congressional and presidential effects on the demand for lobbying. *Political Research Quarterly*, doi:10.1177/1065912909343578.
- Beaver, W. H. (1966). Financial ratios as predictors of failure. *Journal of Accounting Research*, 4(3), 71-111.
- Becker, W. E., Jr. (1983). Economic education research: Part III, statistical estimation methods. *The Journal of Economic Education*, 14(3), 4-15.
- Blaug, M. (1987). *The methodology of economics or how economists explain*. Cambridge: Cambridge University Press.
- Burtini, G. (2008). *Indicators of economic recession*. Retrieved from <http://www.politonomist.com/indicators-of-economic-recession-00272/>.
- Cable News Network. (2010). Fortune 500: A database of 50 years of Fortune's list of America's largest corporations. *CNNMoney.com*. Retrieved from http://money.cnn.com/magazines/fortune/fortune500_archive/letters/M.html.
- Caks, J. (1977). The coupon effect on yield to maturity. *The Journal of Finance*, 32(1), 103-115. Retrieved from <http://www.jstor.org/stable/2326906>.
- Campbell, J. Y. (1995). Some lessons from the yield curve. *The Journal of Economic Perspectives*, 9(3), 129-152. Retrieved from <http://www.jstor.org/stable/2138430>.
- Ceaser, J. W., Thurow, G. E., Tulis, J., & Bessette, J. M. (1981). The rise of the rhetorical presidency. *Presidential Studies Quarterly*, 11(2), 158-171. Retrieved from <http://www.jstor.org/stable/27547683>.
- Chauvet, M., & Potter, S. (2001). Recent changes in the U.S. business cycle. *Manchester School*, 69(5), 481-508.
- Chen, S. (2009). Predicting the bear stock market: Macroeconomic variables as leading indicators. *Journal of Banking & Finance*, 33(2), 211-223.
- Chubb, J. E. (1985). The political economy of federalism. *The American Political Science Review*, 79(4), 994-1015. Retrieved from <http://www.jstor.org/stable/1956245>.
- Cohen, J. E. (1995). Presidential rhetoric and the public agenda. *American Journal of Political Science*, 39(1), 87-107. Retrieved from <http://www.jstor.org/stable/2111759>.
- Conason, J. (2010). *Oil rules: Ineffective regulations, reckless profiteering*. Retrieved from <http://www.expressmilwaukee.com/article-11003-oil-rules.html>.

- Council of Economic Advisors. (2010). Economic indicators. *GPO Access*. Washington, DC: U.S. Government Printing Office. Retrieved from <http://www.gpoaccess.gov/indicators/index.html>.
- Dayton, M., C. (1992). *Logistic regression analysis*. Retrieved from <http://pdfcast.org/pdf/logistic-regression-analysis>.
- Deile, A. J. (2003). The effect of the 1994 redefinition of the Fortune 500 on its usability as a benchmark for corporate profitability. *Journal of Business & Economics Research*, 1(7), 87-96.
- Del Negro, M. (2001). Turn, turn, turn: Predicting turning points in economic activity. *Economic Review*, 86(2), 1-12.
- Dotsey, M. (1998). The predictive content of the interest rate term spread for future economic growth. *Economic Quarterly*, 84(3), 31-50.
- Druckman, J. N., & Holmes, J. W. (2004). Does presidential rhetoric matter? priming and presidential approval. *Presidential Studies Quarterly*, 34(4), 755-778. Retrieved from <http://www.jstor.org/stable/27552635>.
- du Plessis, P. (2010). The stock market: An excellent predictor of U.S. recessions. *Seeking Alpha*. Retrieved from <http://seekingalpha.com/article/59398-the-stock-market-an-excellent-predictor-of-u-s-recessions>.
- Dueker, M. J. (2002). Regime-dependent recession forecasts and the 2001 recession. *Federal Reserve Bank of St. Louis Review*, 84(6), 29-36. Retrieved from <http://research.stlouisfed.org/publications/review/02/11/Dueker.pdf>.
- Edwards, George, C, III. (1996). Presidential rhetoric: What difference does it make? In M. Medhurst J (Ed.), *Beyond the rhetorical presidency* (pp. 199-217). College Station: Texas A&M University Press.
- Eggertsson, T. (2006). On the survival of imperfect institutions. *Revista De Análisis Económico*, 21(2), 13-24.
- Erikson, R. S. (1989). Economic conditions and the presidential vote. *The American Political Science Review*, 83(2), 567-573. Retrieved from <http://www.jstor.org/stable/1962406>.
- Estrella, A., & Mishkin, F., S. (1996). The yield curve as a predictor of U.S. recessions. *Current Issues in Economics and Finance*, 2(7), 1-6.
- Estrella, A., & Trubin, M. R. (2006). The yield curve as a leading indicator: Some practical issues. *Current Issues in Economics and Finance*, 12(5), 1-7.
- Fazzari, S., & Minsky, H. (1984). Domestic monetary policy: If not monetarism, what? *Journal*

of Economic Issues, 18(1, Economic Policy for the Eighties and Beyond), 101-116.
Retrieved from <http://www.jstor.org/stable/4225414>.

Federal Reserve Bank of New York. (2010). *Federal reserve education data*. Retrieved from <http://www.ny.frb.org/education/index.html>.

Federal Reserve Bank of St. Louis (2010). *Federal reserve economic data*. Retrieved from [http://research.stlouisfed.org/fred2/graph/?s\[1\]\[id\]=GDP](http://research.stlouisfed.org/fred2/graph/?s[1][id]=GDP).

Filardo, A. J. (1999). How reliable are recession prediction model? *Economic Review*, 84(2), 35-55.

Filardo, A. J. (2004). The 2001 U.S. recession: What did recession prediction models tell us? *Bank for International Settlements*. Retrieved from <http://www.bis.org/publ/work148.htm>.

Fleming, M. J. (1997). The round-the-clock market for U.S. treasury securities. *Economic Policy Review*. 3(2). 9-32.

Fortune 500. (2010,). Fortune 500: A changing landscape. *CNNMoney.com*. Retrieved from <http://money.cnn.com/magazines/fortune/fortune500/2010/21century/swf/>.

Giacomini, R., & Rossi, B. (2009). Detecting and predicting forecast breakdowns. *Review of Economic Studies*, 76(2), 669-705.

Hailu, A., & Regassa, N. (2007). Correlates of household food security in densely populated areas of southern Ethiopia: Does the household structure matter? *Studies on Home and Community Science*, 1(2), 85-91.

Hale, D. & O'Neill, T. P., Jr. Symposium on the U.S. Congress. (1982). *The United States Congress : Proceedings of the Thomas P. O'Neill, Jr. Symposium on the U.S. Congress, Boston College, January 30-31, 1981*. Chestnut Hill, MA: The College.

Haltmaier, J. (2008). *Predicting cycles in economic activity*. (International Finance Discussion Papers Number 926). The Federal Reserve Board. Retrieved from <http://www.federalreserve.gov/pubs/ifdp/2008/926/ifdp926.pdf>.

Hamberg, U., & Verständig, D. (2009). *Applying logistic regression models on business cycle prediction*. (Unpublished master's thesis, Stockholm School of Economics, Stockholm, Sweden). Retrieved from <http://arc.hhs.se/download.aspx?MediumId=680>.

Hamilton, J. D., & Dong Heon Kim. (2002). A reexamination of the predictability of economic activity using the yield spread. *Journal of Money, Credit and Banking*, 34(2), 340-360.
Retrieved from <http://www.jstor.org/stable/3270691>.

Hansen, A. H. (1964). *Business cycles and national income*. New York: Norton.

- Harrison, E. (2010, November 13). Rosenberg: U.S. GDP is overstated. *Credit Writedowns*. Retrieved from <http://www.creditwritedowns.com/2009/11/rosenberg-u-s-gdp-is-overstated.html>.
- Hasan. (2008, April 1). Re: Fortune 500 companies - what does it take? [Online forum content]. Retrieved from <http://www.dirjournal.com/business-journal/fortune-500-companies-what-does-it-take/>.
- Haubrich, J. G., & Dombrosky Ann M. (2006). Predicting real growth using the yield curve. *Economic Review*, (Q1). 26-35. Retrieved from <http://ideas.repec.org/a/fip/fedcer/y1996iqip26-35.html>.
- Hayashi, F. (2000). *Econometrics*. Princeton, N.J.: Princeton University.
- Hemmerdinger, E. (2008, October 21). *Understanding financial markets: From fear to fluency with Viv's vocabulary*. Women's Voices for Change: Redefining Life after 40. Retrieved from <http://womensvoicesforchange.org/understanding-financial-markets-from-fear-to-fluency-with-viv%E2%80%99s-vocabulary.htm>.
- Hodgson, G. M. (2002). *How economics forgot history: The problem of historical specificity in social science*. London; New York: Routledge.
- Hu, Z. (1993). The yield curve and real activity. *IMF Staff Papers*. 40(4), 781-806. Retrieved from <http://www.jstor.org/stable/3867610>.
- Huitt, R. K. (1954). The congressional committee: A case study. *The American Political Science Review*, 48(2), 340-365. Retrieved from <http://www.jstor.org/stable/1951200>.
- Hulbert, M. (2008, January 8). Can the stock market predict the next recession? *Barron's*. Retrieved from <http://online.barrons.com/article/SB119980107558974769.html>.
- Kallberg, J. G., & Parkinson, K. L. (1993). *Corporate liquidity: Management and measurement*. Homewood, IL: Irwin.
- Kangas, S. (1997). *The great depression: Its causes and cure*. Retrieved from www.huppi.com/kangaroo/Keynesianism.htm.
- Kantor, B. (1979). Rational expectations and economic thought. *Journal of Economic Literature*, 17(4), 1422-1441. Retrieved from <http://www.jstor.org/stable/2723721>.
- Knoop, T. A. (2004). *Recessions and depressions: Understanding business cycles*. Westport, Conn.: Praeger.
- Kobielus, J. (2010). The Forrester wave: Predictive analytics and data mining solutions, Q1 2010. *Forrester Research, Inc*. Retrieved from <http://www.sas.com/news/analysts/forresterwave-predictive-analytics-dm-104388-0210.pdf>

- Kozicki, S. (1997). Predicting real growth and inflation with the yield spread. *Economic Review*,(QIV). 39-57. Retrieved from <http://ideas.repec.org/a/fip/fedker/y1997iqivp39-57nv.82no.4.html>.
- Labaton, S. (2008, October 3). Agency's '04 rule let banks pile up new debt, and risk. *New York Times*, pp. 1-3.
- Labonte, M., & Makinen, G. (2008). *The pattern of interest rates: does it signal an impending recession?* (CRS report for Congress No. RS22371). U.S. Congressional Research Service.
- Lahiri, K., & Moore, G. H. (1991). *Leading economic indicators: New approaches and forecasting records*. Cambridge,[England]; New York: Cambridge University Press.
- Landis JR, & Koch GG. (1977). The measurement of observer agreement for categorical data. *Biometrics*, 33(1), 159-74.
- Levanon, G. (2010). Evaluating and comparing leading and coincident economic indicators. *Business Economics*, 45, 16-27.
- Lewellen, J. (2004). Predicting returns with financial ratios. *Journal of Financial Economics*., 74(2), 209-235.
- Liou, D., & Smith, M. (2006). *Macroeconomic variables in the identification of financial distress*. Working papers series, Social Science Research Network. Retrieved from http://papers.ssrn.com/sol3/papers.cfm?abstract_id=900284.
- Mayer, K., R. (2002). *With the stroke of a pen: Executive orders and presidential power*. Princeton, NJ: Princeton University Press.
- Medhurst, M. J. (1996). *Beyond the rhetorical presidency* (1st ed.). College Station: Texas A & M University Press.
- Meier, K., & Balke, D. (2006). *Developing a credit scoring model for microfinance Bank of Azerbaijan* (LFS Discussion Paper No. 14). Berlin: LFS Financial Systems GmbH.
- Mester, T., Ioana. (2007). Indicator approach to business cycle analysis. *Fascicle of Management and Technological Engineering*, 6(16), 1-7.
- Mill, J. S. (1909). Principles of political economy with some of their Applications to Social Philosophy. In W. J. Ashley (Ed). *Library of Economics and Liberty*. Retrieved from the <http://www.econlib.org/library/Mill/mlP.html>.
- Moe, T. M. (1982). Regulatory performance and presidential administration. *American Journal of Political Science*, 26(2), 197-224. Retrieved from <http://www.jstor.org/stable/2111036>.

- Moench, E. (2008). Forecasting the yield curve in a data-rich environment: A no arbitrage factor-augmented VAR approach. *Journal of Econometrics*, 146(1), 26-43.
- Montier, J. (2009, February 24). The tao of investing: The ten tenets of my investment creed. *World Global Strategy*. Retrieved from <http://www.scribd.com/doc/27599172/James-Montier-10-Tenets-of-Investing>.
- Moore, G. H. (1993). Recessions. *The Concise Encyclopedia of Economics*. Library of Economics and Liberty. Retrieved from the <http://www.econlib.org/library/Enc1/Recessions.html>.
- Moore, G. H., & Zarnowitz, V. (1984). *The development and role of the national bureau's business cycle chronologies*. Cambridge, MA: National Bureau of Economic Research. 146.
- Murphy, J., R. (2010). *Basics of logistics regression* (No. 9). Denver, CO: BERD Education Committee.
- Muth, J. F. (1961). Rational expectations and the theory of price movements. *Econometrica*, 29(3), 315-335. Retrieved from <http://www.jstor.org/stable/1909635>.
- Nadeau, R., & Lewis-Beck, M. S. (2001). National economic voting in U.S. presidential elections. *The Journal of Politics*, 63(1), 159-181.
- Nagler, J. (1994). Scobit: An alternative estimator to logit and probit. *American Journal of Political Science*, 38(1), 230-255.
- Ohlson, J. A. (1980). Financial ratios and the probabilistic prediction of bankruptcy. *Journal of Accounting Research*, 18(1), 109-131. Retrieved from <http://www.jstor.org/stable/2490395>.
- Ostrom, V., & Ostrom, E. (1971). Public choice: A different approach to the study of public administration. *Public Administration Review*, 31(2), 203-216.
- Pampel, F. C. (2000). *Logistic regression : A primer*. Thousand Oaks, CA: Sage Publications.
- Park, C. S. (2002). *Contemporary engineering economics*. Upper Saddle River, N.J.: Prentice Hall.
- Pelaez, R. F. (2007). Ex ante forecasts of business-cycle turning points. *Empirical Economics*, 32(1), 239-246.
- Policy Agendas Project. (2010). *Datasets and codebooks*. Retrieved from <http://www.policyagendas.org/>.
- Ricardo, D. (1810). *The high price of bullion, a proof of the depreciation of bank notes*. London: J. Murray.

- Rogers, R. M. (1998). *Handbook of key economic indicators*. New York: McGraw-Hill.
- Royal Swedish Academy of Sciences (2001, October 10). Popular information: Information for the public.[Press Release]. Retrieved from http://nobelprize.org/nobel_prizes/economics/laureates/2001/public.html.
- Safer, A., M. (2003). A comparison of two data mining techniques to predict abnormal stock market returns . *Intelligent Data Analysis*, 7(1), 3-13.
- Seifert, J. W. (2004). *Data mining: An overview*. (CRS report for Congress No. RL31798). U.S. Congressional Research Service.
- Siegel, J. J. (1991). Does it pay stock investors to forecast the business cycle? *The Journal of Portfolio Management*, 18(1), 27-34. doi:10.3905/jpm.
- Smeeton, N. C. (1985). Early history of the kappa statistic. *Biometrics*, 41(3), 795.
- Smith, S. S., Roberts, J. M. & Vander Wielen, R. J. (2006). *The American Congress*. Cambridge, MA: Cambridge Press.
- Soubbotina, T. P. (2004). *Beyond economic growth an introduction to sustainable development*. Washington, D.C.: World Bank.
- Stuckey, M. (2006). Establishing the rhetorical presidency through presidential rhetoric: Theodore Roosevelt and the Brownsville raid. *Quarterly Journal of Speech*, 92(3), 287-309.
- Sung, T. K., Chang, N., & Lee, G. (1999). Dynamics of modeling in data mining: Interpretive approach to bankruptcy prediction. *Journal of Management Information Systems*, 16(1), 63.
- Tetlock, P., E. (1981). Pre to post election shifts in presidential rhetoric: Impression management or cognitive adjustment. *Journal of Personality and Social Psychology*, 41(2), 207-212.
- The Conference Board. (2010). *Global business cycle indicators*. Retrieved from <http://www.conference-board.org/data/bci.cfm>.
- The National Bureau of Economic Research. (2010). *Statement of the NBER business cycle dating committee on the determination of the dates of turning points in the U.S. economy*. Retrieved from http://www.nber.org/cycles/general_statement.html.
- Thornton, M. (2004). Uncomfortable parallels. *Lewrockwell.com*. Retrieved from <http://www.lewrockwell.com/thornton/thornton21.html>.
- Tjung, L., C., Kwon, O., Tseng, K., C., & Bradley, J. (2010). Forecasting financial stocks using data mining. *Global Economy and Finance Journal*, 3(2), 13-26.

- Topic tracking. (2006, August 17). *Lazine*. Retrieved from www.la.psu.edu/CLANews/Lazine/issue29/issue29.shtml+Lazine%5C+issue+29+baumgartner&cd=1&hl=en&ct=clnk&gl=us.
- Tree, J. (2010). *Recessions and the state of our economy: A visual primer*. Retrieved from <http://www.thedigeratlife.com/blog/index.php/2008/04/21/recessions-and-the-state-of-our-economy-a-visual-primer/>.
- Tulis, J., K. (1996). Revising the rhetorical presidency. In M. J. Medhurst (Ed.), *Beyond the rhetorical presidency* (pp. 3-14). College Station: Texas A&M University Press.
- UCLA Academic Technology Services. (2010). *SAS annotated output*. Retrieved from <http://www.ats.ucla.edu/stat/sas/output/default.htm>.
- U.S. Economics and Statistics Administration. (2010). *Key economic indicators*. Retrieved from <http://www.economicindicators.gov/>.
- U.S. National Archives. (2010). Executive orders faq's. *The Federal Register*. Retrieved from <http://www.archives.gov/federal-register/executive-orders/disposition.html>.
- U.S. Securities and Exchange Commission. (2010). *Electronic data gathering, analysis, and retrieval system*. Retrieved from <http://www.sec.gov/edgar/aboutedgar.htm>.
- Vasisht, A., K. (2010). *Logit and probit analysis*. Retrieved from <http://www.iasri.res.in/ebook/EBADAT/6-Other%20Useful%20Techniques/5-Logit%20and%20Probit%20Analysis%20Lecture.pdf>.
- Weingast, B. R., & Moran, M. J. (1983). Bureaucratic discretion or congressional control? Regulatory policymaking by the federal trade commission. *The Journal of Political Economy*, 91(5), 765-800.
- Windt, T. O., Jr. (1984). Presidential rhetoric: Definition of a field of study. *Central States Speech Journal*, 35(1), 24-34.
- Wood, B. D., & Waterman, R. W. (1993). The dynamics of political-bureaucratic adaptation. *American Journal of Political Science*, 37(2), 497-528. Retrieved from <http://www.jstor.org/stable/2111382>.
- Wright, J. H. (2006). The yield curve and predicting recessions. *FEDs Working Paper*, No. 2006-7.
- Yamarone, R. (2004). *The trader's guide to key economic indicators*. Princeton, NJ: Bloomberg Press.
- Zarefsky, D. (2004). Presidential rhetoric and the power of definition. *Presidential Studies Quarterly*, 34(3), 607-619.

- Zarnowitz, V. (1986). *The record and improvability of economic forecasting*. (NBER Working Paper No. w2099). Cambridge, MA: National Bureau of Economic Research.
- Zarnowitz, V. (1993). *What is a business cycle?* (NBER Working Paper No. w3863). Cambridge, MA: National Bureau of Economic Research.
- Zarnowitz, V., & Moore, G. H. (1982). Sequential signals of recession and recovery. *Journal of Business*, 55(1), 57–85.
- Zelizer, J. E. (2004). *The American Congress: The building of democracy*. Boston: Houghton Mifflin.