

Government Revenue Forecasting During Exceptional Times

by

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A Dissertation Presented in Partial Fulfillment
of the Requirement of the Degree
Doctor of Philosophy

Approved April 2018 by the
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ARIZONA STATE UNIVERSITY

May 2018

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ABSTRACT

Government revenue forecasting errors have become larger, especially in exceptional times such as the periods surrounding economic recessions. Inaccurate revenue estimates stem from unanticipated revenue increases or decreases from a previous trend. Unfortunately, current forecasting methods relying primarily on trend analysis do not incorporate these kinds of sudden changes easily. When revenue punctuations occur, the revenue forecasting errors increase.

To reduce forecasting errors caused by revenue punctuations in government revenue collections, I argued that analysts must not dismiss outliers as extraneous or useless phenomena. My research revealed an approach to incorporate outliers or punctuations into revenue forecasting. First, this research studied the criterion for judging the appearance of revenue punctuations using state governments' quarterly collections of the five largest taxes from 1977 to 2016. Second, the research explored the patterns of these revenue punctuations, specifically the relationship between the changes in dollar amount and the amount of time from one revenue punctuation to another.

Inspired by the few statistical techniques for identifying outliers, this research applied the studentized residuals method to detect the revenue punctuations. The result revealed that all five tax categories for each state have revenue punctuations, except Motor Fuels Tax in the state of Tennessee.

Furthermore, this research disclosed that while not all the states and all the tax categories have statistically significant relationships between the depth and length of revenue punctuations, some states still have valid relationships. For the states that have statistically significant relationships, a forecaster, knowing depth, could calculate length

and vice versa. Thus, the forecasting errors caused by revenue punctuations could be reduced when the protocols my research identified are used.

To my darling parents, and my dear husband for all the support you provided to me during this backbreaking journey. Without your love and encouragement, I could not pursue this dream and achieve my goal. Thank you!

ACKNOWLEDGMENTS

At this very significant juncture on my journey to complete my doctorate degree, I would like to express my deepest appreciation to my committee chair, Professor Gerald J. Miller for his continuous support and encouragement during my Ph.D. studies and related research, and for his kindness, patience, motivation, and vast knowledge. His guidance and help were critical for the completion of this dissertation. I cannot have imagined how my dissertation would be without him.

I would also like to thank the rest of my dissertation committee. Professor Gerald, Zhiyong Lan, and Professor Jeffery R Wilson, provided their unparalleled expertise and insight, and also asked questions that inspired and motivated me to expand my research in unique ways.

My sincere thanks also goes to all the professors, staff, students, and my Ph.D. cohort at the School of Public Affairs, who provided me endless guidance, assistance and support. Without their valuable support, it would not be possible for me to complete this dissertation.

I am grateful to the management teams at the Budget and Research Department of the City of Phoenix and Arizona Department of Health Services Department. Thank you for allowing me to have a flexible working schedule while attending school, teaching classes, meeting with professors, and writing my dissertation. Also, I would like to extend my thanks to my coworkers for their moral support. Their support helped me to complete this dissertation.

Last but not the least, I would like to thank my family. My parents and my husband supported me spiritually throughout writing this dissertation and encouraged me to achieve my goal.

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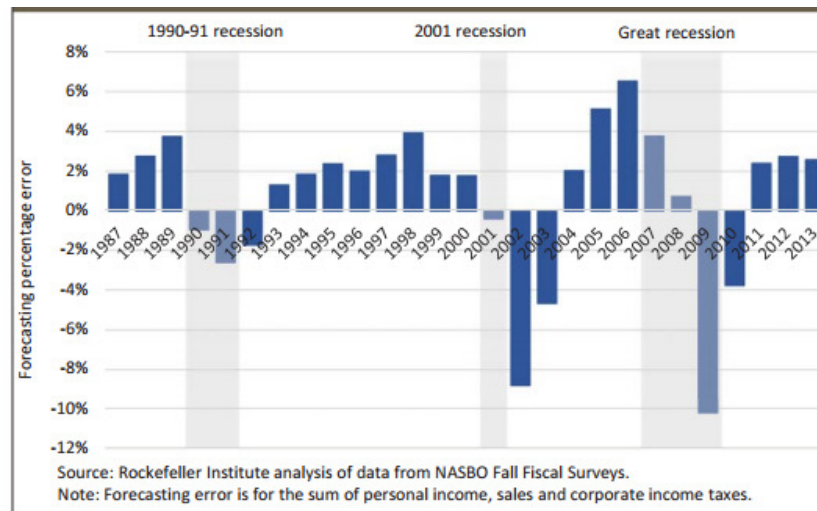
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CHAPTER 1

INTRODUCTION

Many if not most states have failed to estimate their tax revenue accurately. *Governing* magazine considers state revenue projections to be a significant issue for states in 2018 (Farmer, 2018). *The Washington Post* reported that “U.S states are getting worse at projecting tax revenue” (Chokshi, 2015). The budgeting and finance policy researchers Donald J. Boyd and Lucy Dadayan at the Rockefeller Institute of Government at the State University of New York found that forecasting errors have become more substantial, and tax revenue is more difficult to predict (2014). In addition, they found that projections became even worse around recessions. See the Figure 1.1 below.

Figure 1. 1: The Median State Revenue Forecasting Errors from 1987 to 2013



Source: Boyd and Dadayan, 2014, p.8, Figure 2

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Figure 1.1 above displays tax revenue forecasting errors in the United States, according to the Rockefeller Institute of Government’s research. In the figure, Boyd and

Dadayan compared the actual collected revenues with the estimated revenues and calculated the forecasting error rates. Before recessions, actual collected tax revenues were always more than their estimates, while after recessions actual collected revenues were less than the estimates. This problem became even worse around the latest two recessions. Affected by the 2001 Recession, the error rates for 2002 and 2003 increased dramatically. Affected by the Great Recession, the error rates for 2006, 2007, 2009, and 2010 also had surged significantly.

Why are states getting worse at predicting tax revenues? Boyd and Dadayan argued that growth of revenue volatility is the major reason for rising forecasting errors (2014). They cited William Mark Crain's definition of revenue volatility, which is "the standard deviation of the deviation in revenue from its long-run trend line" (Crain, 2003, p.74).

From a public policy perspective, revenue volatility could be considered as revenue punctuations. Frank R. Baumgartner and Bryan D. Jones stated that policy processing contains long periods of stability and bursts of dramatic changes, and dramatic changes are called punctuations (Baumgartner & Jones, 2009). Looking at a specific area of public policy, for instance, in the tax revenue field, volatility reveals punctuations. Revenue volatility could be caused by factors like unexpected economic turns, new legislation, and changes in federal policy. All of these factors are reflected as punctuations in tax revenue collection. The Rockefeller Institute of Government's report showed that standard deviation used for measuring volatility of tax collection has increased from below 3.5 percentage points every year to 6 percentage points each year between 2009 and 2011 (Boyd & Dadayan, 2014), which means more punctuations have

appeared. Punctuations change the trend. As such, the prior trend might not be useful for analysis.

With the evidence of rising revenue volatility and the forecasting errors that follow, current projection methods seem to have failed to confront revenue punctuations. Most commonly, revenue is projected based on the predicted population, wages, employment, personal income, interest rates, consumer confidence levels, gross national product, gross domestic product, stock market performance, and specific important factors for states or cities (Boyd & Dadayan, 2014). Beyond these economic factors, estimation models also include factors like tax returns to be filed in the forecasted year, and tax policy changes in the past year.

However, there are several problems with these methods when revenue punctuations occur. *First*, the revenue estimate is based on the predicted economic factors. If the projection of economic factors fails to capture economic punctuations, a revenue projection will not include punctuations either. *Second*, some important factors related to punctuations might not be included as independent variables in the estimation models because researchers are not able to collect the data, or these factors are otherwise unknown to the researchers. For example, an economic crisis might contribute to revenue punctuations. However, economic crisis is hard to predict and is rarely included in the revenue forecasting model. *Third*, most revenue estimation is built with econometric models. The essence of econometrics is to analyze the dominant distribution, but ignore outliers. Revenue punctuations are the outliers, and econometric models may not be suitable to analyze them. If revenue punctuations have profoundly affected the accuracy of revenue projection, and current methods have failed to suggest how to analyze the

revenue punctuations, what methods could be utilized for analyzing tax revenue punctuations to reduce forecasting errors?

Given the above question in mind, consider the similarity between tax revenues and stock prices. Both are highly affected by volatile economic, legislative and administrative changes, and dependent on the idiosyncratic behavior of either taxpayers or investors. Researchers might apply methods for stock market analysis to tax revenue analysis, specifically tax revenue punctuations.

There are two significant methodologies for stock market analysis: *fundamental analysis and technical analysis*. *Fundamental analysis* is very similar to the current revenue estimation methods, which is based on analyzing the factors that affect stock prices and using them to project the performance of stock market. *Technical analysis* studies the stock price movement in the charts, and uses patterns and charts to project future price movement. Since fundamental analysis already fails to study revenue punctuations, this research mainly focuses on technical analysis.

Despite the promise found in technical analysis, two problems remain in forecasting revenues during punctuation caused by any factor, turning points, and punctuation patterns. First, it is difficult to project the turning points of revenue punctuations correctly. Turning points are points where revenue suddenly and significantly changes from an increase to decrease, or from decrease to increase. Second, even with technical analysis, Paul Samuelson commented that the “stock market forecast nine of the last five recessions” (as quoted in Liesman, 2016), which is about a 50% error rate. Therefore, this research will not focus on predicting the turning points of revenue

punctuations. Others, such as Joseph E. Stiglitz are pioneering work in this area (Stiglitz, 2015).

Instead, this research investigates revenue punctuations' patterns, especially exploring the criteria and rules for judging the appearance of revenue punctuations, their depth and length and whether their depth has a relationship with their length. The specific research questions are:

1. Is there a criterion to judge the appearance of revenue punctuations?
2. Is there a relationship between the depth and length of revenue punctuations?

With the findings of this research and by observing revenue changes, estimators can identify whether a data point is a revenue punctuation point. Also, the forecaster could determine how much the revenue will increase or decrease from one revenue punctuation to another revenue punctuation. Estimators could then separate revenue punctuation analysis from the regular incremental forecasts, and revenue estimation errors will decrease.

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For Figure 2.1: Leptokurtic Distribution for Punctuated Equilibrium, Dr. Frank R. Baumgartner wrote: "Thanks for your note about reproducing a figure from my 2013 paper with Derek Epp. I'm glad it's useful to you. Feel free to use it in your dissertation".

For Figures 2.2-2.9 are from Murphy's Book Technical Analysis of the Financial Maker. The permission letter is below.



September 27th, 2016

Dan Wang

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CHAPTER 2

LITERATURE REVIEW

In this section, literature on four topics will be reviewed: 1) punctuated equilibrium theory in public policy field, 2) studies of punctuated equilibrium in public finance field, 3) current revenue forecasting methods, and 4) the methods that might be used for forecasting when revenues are volatile.

First and foremost, this section starts with a general overview of punctuated equilibrium theory in public policy field. With evidence from various public policy areas, the review reveals that punctuated equilibrium is omnipresent. *Second*, I study a specific area of policy: the public finance field. My investigation confirms that the public finance field (tax revenue collection) has addressed punctuated equilibria. *Third*, I scrutinize the current revenue projection methods and find that the current methods for revenue forecasting fail to project revenue punctuations. *Last but not least*, I study other fields, especially technical analysis of markets, and try to find methods that might be used for analyzing revenues punctuation, or at least help us learn the patterns of revenue punctuations and the relationship between the severity and duration of revenue punctuations.

2.1 Punctuated Equilibrium in Public Policy Field

This section will review the policy process by first introducing the theory of incrementalism. Because of the failure of incrementalism, punctuated equilibrium theory appears and has been proved insightful in various policy areas.

In the public policy field, represented by Charles E. Lindblom and Aaron Wildavsky, incrementalism had dominated for several years. Lindblom argued that due to

limited knowledge and resources, “we coordinate each new decision with past decisions of ourselves and others to the extent that we take the status quo, which is the product of past decisions, as the real world to which our decision has to be adapted” (Lindblom, 1965, p.10). Furthermore, Lindblom contended that within different interest groups, the partisan adjusters always look for “a solution which is to the advantage of some and a loss to none,” that is called the Pareto optimum (Lindblom, 1965, p.210). To achieve this optimum, Lindblom stated that interest groups “mutually adjust” their policy positions, and through compromise, encourage government policy decisions to follow an incremental change path. In other words, Lindblom believed that because of cognitive limitation and conflicts between interest groups, incrementalism had been widely applied in the public policy process.

Wildavsky applied the idea of incrementalism to the budgetary process. He and his students Otto A. Davis, and M. A. H. Dempster (1966) utilized 17 years of time-series data for fifty-six non-defense agencies of the U.S. government and found that prior year appropriation plays a significant role in current year budgetary decision making. Administrators consider the prior year’s appropriation as the baseline, and the final budgets only contain incremental and small changes to the baseline.

However, many scholars and researchers argue that incrementalism neglects large-scale changes, and a substantial amount of criticism has emerged. For instance, John W. Kingdon (2003) argued that once the problem is defined (problem stream), a solution to the problem has been developed (policy stream), and political supports have been gained (politics stream), the policy windows are open, which may cause dramatic changes in public policy. This is also called “windows of opportunity” theory. To

Kingdon (2003), the defined problem could be that the cost of medical care is too high and the public is starting to complain. Policy entrepreneur and policymaker then provide a solution by introducing incentives into the medical system to promote market regulation. The new administration was just elected and would like to make some changes and support the proposed solution. Thus, it is very likely to have a sudden health policy change. The “windows of opportunity” theory illustrates that incremental changes may not always be accurate, sudden dramatic changes do happen in the public policy field.

In the 1990s, Baumgartner and Jones realized that policy development does not only include one phase: incremental changes, or dramatic changes. Instead, policy development contains both incremental and dramatic changes. Inspired by evolutionary biology, Baumgartner and Jones introduced punctuated equilibrium theory to the public policy field. They stated that policies develop over long periods of stability and bursts of dramatic change. The long periods of stability are called equilibria, and dramatic changes are called punctuations (Baumgartner & Jones, 2009).

Baumgartner and Jones (2009) conducted a great deal of empirical research and proved that punctuated equilibrium does appear in various areas of public policy making. For instance, with the data of U.S. federal spending and budget changes from 1791 to 2000, Baumgartner argued that federal expenditures and budgets generally have a steady, linear growth, but the dramatic adjustments are surprisingly common. He contended (Baumgartner, 2013) that:

Typically, we expect from government a similar array of goods and services as we had expected in the previous year. Occasionally, we dramatically change our

expectations. Demonstrated failure of the status quo (through the outbreak of war) may have a lot to do with this. (pp. 244-245)

Because of the dramatic changes Baumgartner mentioned, he proposed that budget allocation should be separated into two categories: small adjustments (minor demands) and larger reallocations (major demands). For the small adjustments, decision making may not involve outside political actors (such as the president), while for the larger reallocations, higher-level political actors like the president are involved. In addition, Baumgartner posited that if there is no crisis, a budget allocation will have marginal and incremental adjustments. However, when policies are perceived to have failed, then budget allocation will have major adjustments (Baumgartner, 2013).

2.2 Studies of Punctuated Equilibrium in Public Finance Field

The previous section reviewed the general application of punctuated equilibrium theory. This section will examine the tax and revenue field, and attempt to determine whether punctuated equilibrium is recognizable in this specific area of public policy.

In the tax and revenue field, studies of punctuated equilibrium give particular attention to revenue stability and volatility. Equilibrium is represented by revenue stability: incremental revenue increases or decreases incrementally. Punctuations refer to revenue volatility or sudden changes in the amount of revenue collected.

The studies dated back to the 1950s. One of the first substantive studies on the subject was conducted by Harold M. Groves and C. Harry Kahn (1952). Groves and Kahn found income to be one of the major factors that influence the stability of tax collections. However, they also found that not all taxes are affected by income change. Groves and Kahn categorized taxes into three groups, according to whether changes in

income could affect the stability of tax collections. The first category refers to low-income elasticity taxes, which have no or minimal relationship with income changes. To Groves and Kahn, these taxes are stable. In punctuated equilibrium theory, such taxes are considered to be at equilibrium because the taxes will not fluctuate according to income changes. Examples of this could be certain types of local licenses and the property tax.

The second category is the medium income elasticity taxes, which have proportional changes when income changes. An example of this category could be sales tax.

The third category represents high-income elasticity taxes that have a strong relationship with income changes. Groves and Kahn considered these taxes to be unstable because any changes in income could cause changes in tax collections. Examples of this include individual and corporate income taxes (Groves & Kahn, 1952). Because income has a strong relationship with income taxes, if there are punctuations in income (such as recession and stock market crashes), income taxes will change from stasis to volatile. The entire tax system becomes unstable if income taxes occupy a significant portion of it.

William F. Fox and Charles Campbell (1984) found that even though sales taxes are not so sensitive to income punctuations in the long run, in the short run, they are still unstable because they are profoundly affected by the fluctuations of the business cycle. Their research suggested that both income taxes and sales taxes have punctuations.

Fred C. White found that state and local governments started to substitute stable taxes for fast-growing but unstable taxes (1983). This activity rapidly increased the revenue yields for state and local governments, but subsequently added more volatility to the tax structure. This volatility is due to the fast-growing taxes, such as personal and

corporate income taxes, are most responsive to the short-run business cycle. Taking the state government of Georgia as an example, using standard deviations to measure tax instability, White found that there are trade-offs between the growth and stability of seven major taxes in Georgia. He recommended a diversified tax structure that has both stable and volatile taxes, and also balances tax growth and stability (White, 1983).

Richard F. Dye and Therese J. McGuire also studied the relationship between the growth rate and stability of tax revenues (1991). In contrast to White, Dye and McGuire focused on general sales and individual income taxes. They argued that total consumption expenditure is the primary factor that affects general sales tax collection. Although sub-categories of total consumption expenditure are volatile, it remains stable over years. In addition, they contended that general sales taxes could be separated into taxes on goods and taxes on services. As a result, the trade-off between growth and stability may not hold for taxes on services. For instance, their analysis suggested that recreation services spending could grow quickly but remain stable.

In the 1990s, Russell S. Sobel and Randall G. Holcombe (1997) argued that tax revenues differ from tax bases both by definition and by their impact on elasticity. By definition, tax revenues are the result of tax bases multiplied by tax rates. As for impact, Sobel and Holcombe (1997) suggested that:

Although there are some significant differences among the individual states..., looking at overall averages cyclical variability estimates are not reduced when looking at revenues rather than tax bases, implying that state tax code changes cannot significantly reduce revenue variability. (p. 41)

Therefore, they advised that, when estimating tax revenue elasticity, forecasters need to concern with both tax policy changes to the base as well as to the rate.

The previous research studied the factors that affect tax collections, the tradeoffs between tax growth and stability, the methods for reducing revenue volatility, and recommended the consideration of tax policy changes to both base and rate when forecasting tax revenues. Regardless of the areas on which scholars focused, their research showed that revenues have stability as well as volatility. In other words, researchers recognize that punctuated equilibrium does exist in the tax and revenue field. However, the implications for revenue estimators seem to have been left untouched.

2.3 Current Revenue Projection Methods

According to the Rockefeller Institute of Government's report discussed in the introduction to this dissertation, tax revenues are even more volatile around recessions, and tax revenue volatility is one of the most important factors affecting the accuracy of revenue projections (Boyd & Dadayan, 2014). Whether scholars and practitioners estimate the impact of revenue volatility and punctuations in their tax revenue projections, becomes an important question. In this section, I will review two mechanisms commonly used today by government forecasters - time-series and econometrics - that suggest forecasters do not recognize punctuations. In addition, I will also discuss the drawbacks of these two mechanisms when they are used to study revenue volatility.

a) Time-Series:

According to Gloria A. Grizzle and William Earle Klay, the time-series approach "extrapolates previous annual revenues to forecast revenues for the next year" (1994). It

includes seven methods, which are i) penultimate year method, ii) the moving average method, iii) average change method, iv) exponential smoothing method, v) linear exponential smoothing method, vi) linear regression method, and vii) curve fitting method (1994).

The penultimate year method projects that the next year's revenue is equal to the previous year's revenue (Grizzle & Klay, 1994). For instance, if the previous year's revenue is \$1 billion, then the next year's revenue is projected to be \$1 billion. It is the simplest method in revenue projection, and the only information needed for projection is the previous year's revenue.

The moving average method refers to projecting the coming year's revenue based on the average of several prior years' revenue (Grizzle & Klay, 1994; Kravchuk & Stone, 2010). For example, if the revenue from the previous three years' is \$0.8 billion, \$1.2 billion, and \$1.6 billion respectively, the forth year's revenue is projected to be \$1.2 billion, which is the average of the past three years' revenues.

The average change method calculates the percentage change from one year to next and uses the average of these percentage changes as the current year's change rate to project the next year's revenue (Grizzle & Klay, 1994). If the prior three years' revenues are \$0.8 billion, \$1.2 billion, and \$1.6 billion, the percentage changes are 50% and 33.3%, respectively. The average change rate of 50% and 33.3% is 41.65%, so the coming year's revenue is projected to be \$2.26 billion ($=\$1.6 \text{ billion} + \$1.6 \text{ billion} \times 41.65\%$).

Compared to the three methods mentioned above, *the exponential smoothing method* requires more statistical analysis. Robert G. Brown proposed this method in the

1950s. The first step in this method is to forecast the current year's revenue based on the historical trend. The second step is to find the difference between the forecasted revenue and the actual revenue. The third step is to forecast the following year's revenue based on the weighted difference between the projected and actual current year's revenue. The criterion for selecting weight is to minimize the mean square error (Grizzle & Klay, 1994). Computer programs could select the weight easily. The formula for the exponential smoothing method is as below:

$$F_t = F_{(t-1)} + \alpha (A_{(t-1)} - F_{(t-1)})$$

F_t is the forecasted revenue, while $F_{(t-1)}$ is the prior year's forecasted revenue. $A_{(t-1)}$ is the prior year's actual revenue, and α is the weight, which is between 0 and 1.

Charles C. Holt developed the linear exponential smoothing method. By adding a statistically computed component to exponential smoothing, the linear exponential smoothing method allows for the forecasting of data with a trend (Chase, 2013).

The next two time-series methods are related to regression analysis. *The simple linear regression method* studies the trend of the historical revenue. With the least-squares technique, the slope of the trendline is selected with the criterion that the sums of the squared errors are minimized.

The curve fitting approach also applies the regression analysis but fits the trend with curves instead of straight lines (Grizzle & Klay, 1994). In addition to Grizzle and Klay's seven methods of time-series analysis, George Box and Gwilym Jenkins popularized the Autoregressive Integrated Moving Average method (ARIMA), which combines the moving average method and autoregressive method (1976). No matter

which method is chosen to project the revenue, the hallmark of the time-series analysis is to project revenue based on historical trends (Bretschneider & Schroeder, 1985).

Time-series analysis fails to help estimate punctuated movements. Because the hallmark of the time-series analysis is to project revenue based on historical trends, time-series analysis is accurate to project incremental changes. However, if the historical trend only has incremental changes but no punctuations, time-series models cannot project sudden changes in the future. In addition, even though the historical trend has punctuations, time-series models focus on the average of the revenue trend, and punctuations might be either “averaged out”, or dropped from the analysis because punctuations might be considered as outliers in the statistical analysis. As a result of these problems, time-series-based forecasting fails to help understand the punctuations’ depth and length, leading to forecast errors the Rockefeller Institute of Government study revealed. In summary, time-series models have failed when studying the revenues that have punctuations.

b) Econometric Approach:

The other mechanism that has been widely used to project revenue is the econometric approach. In this approach, revenue is not the only variable in the analysis, other variables that have correlative or causal relationships have been included in the analysis as well. For example, Groves and Kahn (1952), White (1983), Fox and Campbell (1984), Bretschneider and Schroeder (1985), Dye and McGuire (1991), Sobel and Holcombe (1997), Hou and Seligman (2007), Stephen C. Cooke and Christopher S. McIntosh (2011), and Rockefeller Institute of Government (States & Government, 2011), use economic variables such as gross national product, personal income, and

unemployment rate to project the revenue, while other scholars like John L. Mikesell and Justin M. Ross (2014), Richard T. Boylan (2008), and Daniel L. Smith (2007) found that beyond economic factors, the political acceptance, political distortions, rules, particular participants, and executive politics all impact revenue collection.

In contrast to time-series methods, econometric methods can be more than just methods for forecasting revenues; they can show the relationship between revenue and other variables, and serve as a planning guide for officials (Richardson & Scott, 1978). Furthermore, looking at the perspective of studying punctuations, econometrics methods could project punctuations if the independent variables have punctuations, while time-series approach cannot project punctuations if punctuations have been treated as outliers.

However, not all the independent variables may have punctuations. If the independent variables do not contain punctuations, or even if the independent variables have sudden changes such as economic crises, but the predicted independent variable in the forecast model does not contain punctuations, the revenue projection cannot forecast punctuations accordingly either. Furthermore, some of the factors that could cause or affect revenue punctuations are unknown by the forecasters, or even if they are known, the data are hard to collect.

Moreover, the problems with time-series models on projecting punctuations also apply to econometrics methods. Punctuations could be either “averaged out”, or dropped from the analysis because a punctuation might be considered so unusual a phenomenon that its occurrence is a random event and therefore irrelevant in the statistical analysis.

To increase the accuracy of revenue forecasting, most state and local governments use both time-series and econometric approaches to project revenue. The

current methods might be good to project incremental changes but are not good to study or project punctuations. The Rockefeller Institute of Government's report argued that the errors in revenue projection have worsened progressively during fiscal crises (2011), and a fiscal crisis is one example of a punctuation. The latest crisis provides evidence that the time-series and econometric approaches fail because they could not successfully project revenue punctuations. As a result, the forecasting errors become larger.

2.4 Methods for Studying Revenue Punctuations

In this section, I will explore the public policy field, the statistics field, and the corporate finance field to see whether they have effective methods for analyzing revenue punctuations, specifically studying the criteria and rules used to judge the appearance of revenue punctuations and relationships between their severity and duration.

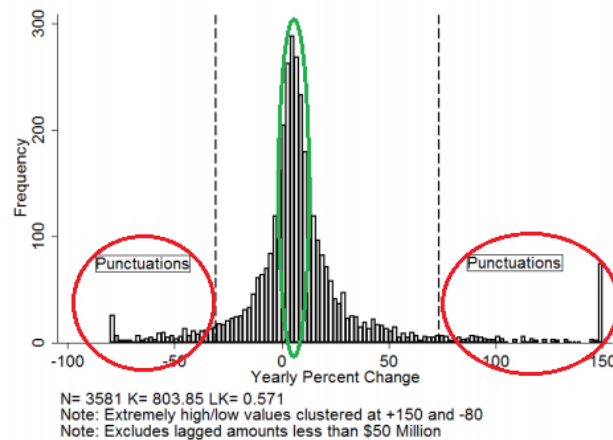
a) Public Policy:

Among public policy research methods, I agree that there is no effective approach for studying the criteria and rules used to judge the appearance of revenue punctuations and relationships between the severity and duration of revenue punctuations.

Baumgartner and Jones introduced punctuated equilibrium theory into the public policy field. However, scholars mainly focused on proving the wide application of punctuated equilibrium in public policy field, studying why punctuations exist in public policy, and what factors might cause punctuations, such as economic crises and policy changes (Baumgartner & Jones, 2009; Breunig & Koski, 2006; Dye & McGuire, 1991; Fox & Campbell, 1984; Groves & Kahn, 1952; Holcombe & Sobel, 1997; Hou & Seligman, 2007; White, 1983).

Little attention, however, has been paid to measuring punctuations. In addition, these scholars analyzed both punctuations and static processes together. For instance, Baumgartner believed the entire punctuated equilibrium process follows a leptokurtic distribution, which has a large central peak for incremental changes (the second circle in the middle area on Figure 2.1) and fat tails for punctuations (the first and third circles on Figure 2.1)(Baumgartner & Epp, 2013,p.4). The leptokurtic distribution could display the distribution of punctuations and incremental changes at the same time. However, there is no specific way to study the punctuations only, not to mention the measurement of the length and depth of punctuations.

Figure 2. 1: Leptokurtic Distribution for Punctuated Equilibrium



Source: Baumgartner & Epp, 2013, p. 4, Figure 1

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Some researchers in public policy field have studied punctuations. However, they only measured the severity of the punctuations, the duration of punctuations or the relationship between the severity and duration of punctuations still lacks study. For instance, Crain constructed an indicator of revenue volatility as, “the standard deviation of the deviation in revenue from its long-run trend line” (p.74). With the measurement of

revenue volatility, the severity of punctuations could be known by comparing the volatility score: the higher score, the more volatile. Christian Breunig and Chris Koski used the L-moment of the Kurtosis score to measure the budget punctuations. According to Bruning and Koski, the L-moment of Kurtosis score is “a descriptive statistic that provides a summary measure of the shape of a distribution” and could be used to measure punctuations (p.372). The L-moment of Kurtosis score ranges from 0 to 1. Like the revenue volatility score, the higher score, the more volatile (Breunig & Koski, 2006). However, these researchers studied only the severity of the punctuations. The duration of revenue punctuations was not studied and neither was the relationship between the severity and duration.

The Rockefeller Institute of Government’s report also only focused on the severity of the punctuations. Although the Rockefeller Institute of Government’s report studied the punctuations by calculating each state’s overall volatility score (the calculation is based on the standard deviation of year-over-year percent change of its total tax revenue) (Bailey & Erford, 2015), the relationship between the severity and duration of punctuations was still not discussed.

b) Statistics:

In statistics, punctuations are defined as outliers. An outlier is “an observation that deviates so much from other observations as to arouse suspicion that it was generated by a different mechanism” (Hawkins, 1980, p.1). Here, a different mechanism could be a new independent variable that affects the dependent variable, or a dramatic change to the existing independent variable. Because of the similarity between punctuations and outliers, the research methods for outliers could be applied to studying punctuations.

However, in statistical analysis, Jason Osborne and Amy Overbay contended that outliers are caused by data errors, intentional or motivated misreporting, sampling error, standardization failure like unusual phenomena, faulty distributional assumptions, and legitimate cases sampled from the correct population (2004).

When outliers are caused by errors or misreporting, in most of the cases these outliers are removed from the analysis. When outliers exist for unclear reasons or legitimate cases sampled from the correct population, they are kept in the analysis. Although there are various reasons causing outliers, statisticians always focus on the majority trends instead of outliers. Furthermore, outliers are always less common, and easily mitigated by majority trending data. Therefore, it seems there is no statistical method being used to study the patterns of outliers or punctuations.

c) Corporate Finance:

The question for this research becomes one of how – how can government revenue punctuations be studied to lessen revenue forecasting errors? One source is existing research in corporate finance. Benoit Mandelbrot and Richard L. Hudson (2006) posited that price movements in the stock market do not always follow the normal distribution assumed by modern finance; they are often discontinuous with significant changes. The major central peak area in a normal distribution refers to the incremental changes; small fat tails could represent the punctuations. However, if there are too many punctuations and the distribution could be changed to non-normal distribution. Since the U.S corporate equities price changes also have incremental as well as punctuated features, maybe researchers can use the methods of analyzing the stock market for studying punctuations.

There are two primary methods for U.S. corporate equities analysis: fundamental and technical. Fundamental analysis is very similar to the econometric approaches used to project revenue, which is based on analyzing the factors that affect stocks and use them to project the performance of the stock market. The technical analysis approach, studies the stock price movements in the charts and uses patterns and charts to project future stock price movements. Since fundamental analysis does not directly study punctuations, this research focuses on whether technical analysis can be utilized to study the punctuations.

According to Robert D. Edwards, John Magee, and, W. H. C Bassetti (2013), technical analysis refers to:

The science of recording, usually in graphic form, the actual history of trading (price changes, volume of transactions, etc.) in a certain stock or in ‘the Averages’; and then deducing from that pictured history the probable future trend (Edwards, Magee, & Bassetti, 2013, p.4).

In other words, technical analysis studies the market itself and exclude any outside factors, such as economic or political factors that influence stock prices. Public finance, as opposed to corporate finance, does not use technical analysis. According to Nada Petrusheva and Igor Jordanoski, technical analysis is still one of “the two main schools of thought and strategies in financial markets” (2016).

John Murphy contended that there are three premises that technical analysis approach is based on, which he also called the philosophy or rationale of technical analysis (Murphy, 1999). *First*, “market action discounts everything” (Murphy, 1999, p.2). This means that even though the market is affected by all kinds of factors including

the economy, politics, and investors' behaviors. These factors are all reflected by stock price changes. In addition, prices also indicate the supply and demand of the market. If supply is greater than demand, prices will drop, and vice versa. Therefore, study charts of prices make sense. Furthermore, because stock prices in the market count everything, without knowing the reasons of price changes, chartists could project the direction of the market by looking at and analyzing trends and patterns (Murphy, 1999).

Second, “price moves in trend”, which means “a trend in motion will continue in the same direction until it reverses” (Murphy, 1999, p.4), and Murphy contended that Newton's first law (“every object will remain at rest or in uniform motion in a straight line unless compelled to change its state by the action of an external force”) (NASA, 2015) could support it.

Third, “history repeats itself.” Because people always learn from past experience, the past will direct future behavior, and history repeats itself.

There are two major techniques used for technical analysis: trend analysis and chart pattern analysis.

Trend Analysis:

According to Murphy, a trend is defined as the direction of the market, which constitutes a series of successive waves with apparent peaks and troughs (1999). There are three directions of a trend: uptrend, downtrend and sideways.

Figure 2. 2: Trend Directions: Uptrend, Downtrend, and Sideways.

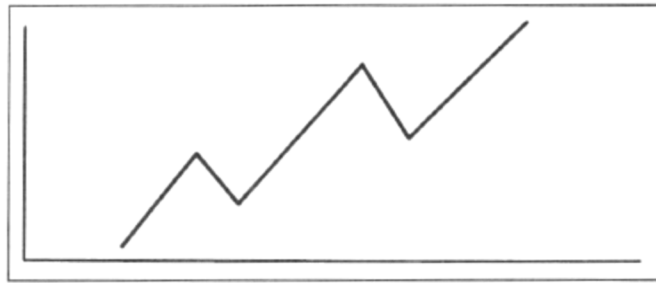


Figure 4.1a
*Example of an
uptrend with
ascending peaks
and troughs.*

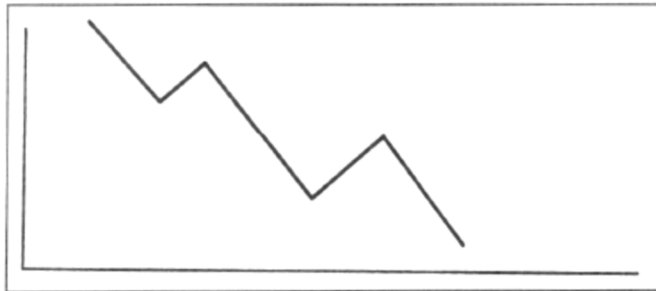


Figure 4.1b
*Example of a
downtrend with
descending peaks
and troughs.*

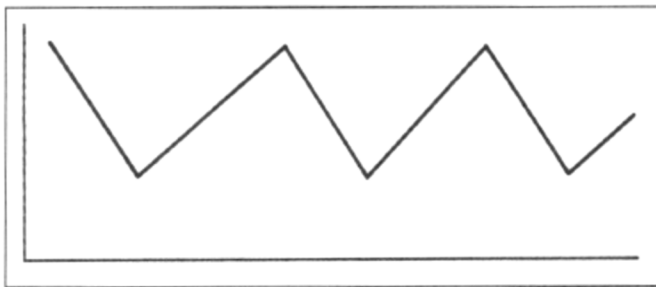


Figure 4.1c
*Example of a
sideways trend
with horizontal
peaks and
troughs. This
type of market is
often referred to
as "trendless."*

Source: Murphy, 1999, p. 50, Figure 4.1a to 4.1c

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Uptrend is defined as a “series of successively higher peaks and troughs” (please refer to Figure 2.2), whereas a downtrend is “a series of successively declining peaks and troughs” (1999, p.50) (please refer to Figure 2.2). Uptrends signify a bull market in which succeeding peaks should always be higher than the previous peaks and troughs, which also indicate investors should buy. Downtrends signify a bear market, and succeeding peaks and troughs are always lower than their predecessors. Downtrends signal to

investors to sell. Sideways trends refer to horizontal peaks and troughs (please refer to Figure 2.2), and usually, chartists do nothing during this kind of period. When uptrend switches to downtrend with a substantial amount change, or downtrend switches to uptrend with a substantial amount change, punctuations or special events may occur.

The other important concept of trend analysis is support and resistance. Support is the bottom line of the stock prices for a certain time, which indicates that buying interest at this level could still overcome the selling pressure, and stocks price for that period are always higher than support level (Edwards et al., 2013; Murphy, 1999). Please see the support line in Figure 2.3 below.

Figure 2. 3: Resistance and Support

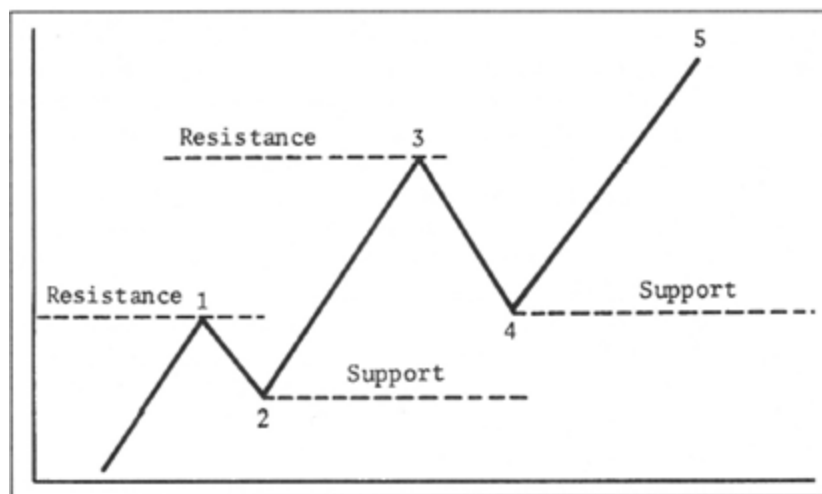


Figure 4.3a Shows rising support and resistance levels in uptrend. Points 2 and 4 are support levels which are usually previous reaction lows. Points 1 and 3 are resistance levels, usually marked by previous peaks.

Source: Murphy, 1999, p.55, Figure 4.3a

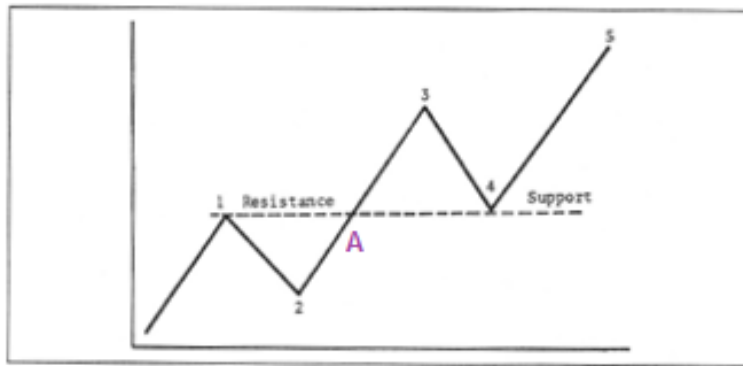
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Resistance refers to the ceiling of the stock price. Sometimes, the stock prices will not move beyond the ceiling, implying that the selling pressure overcomes buyer interest.

Please see the resistance line in Figure 2.3 above.

However, if the resistance line is broken, then the resistance line could become a support line. For instance, in Figure 2.4 below, point A indicates the price break. Before point A, the dotted line is the resistance line, and no price exceeds this line. After the broken point A, the price moves up and the previous resistance line becomes the support line. There is no price below this line.

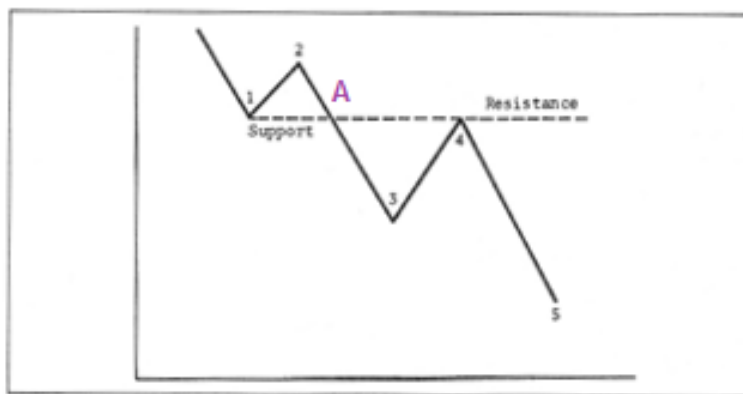
Figure 2. 4: Resistance Reversed to Support



Source: Murphy, 1999, p.62, Figure 4.5a

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Figure 2. 5: Support Reversed to Resistance



Source: Murphy, 1999, p.62, Figure 4.5b

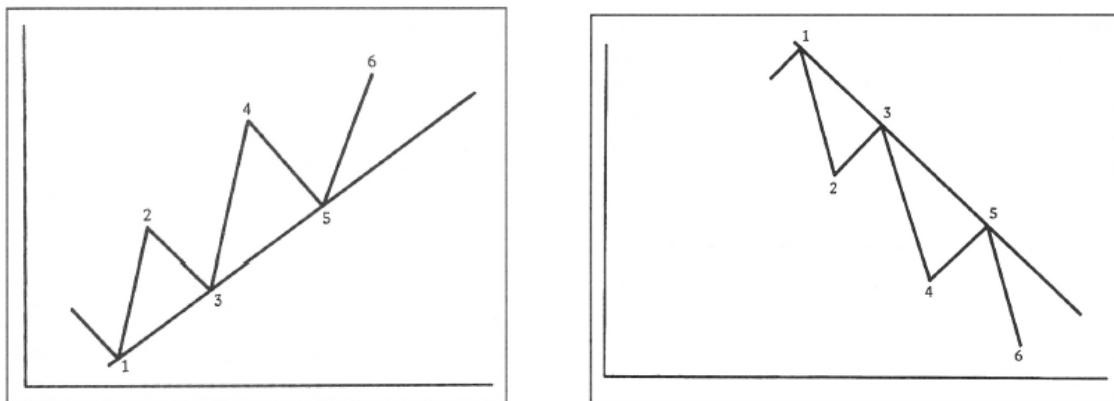
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If the support line is broken, then the support line could become the resistance line. For example, in Figure 2.5 above, point A indicates the price break. Before point A, the dotted line is the support line, and no price drops below this line. After the broken point A, the price moves down, and the previous support line becomes the resistance line, and no price exceeds this line.

Murphy recommended two items to look at before confirming support or resistance level. *First*, the time that stock prices stay in the support or resistance level. The longer they stay, the more significant the support or resistance level is. *Second*, the trading activities around support and resistance level. The trading activity is also called volume in technical analysis. Heavy volume around support and resistance level could help confirm the support and resistance level.

Another essential tool for technical analysis is the trendline. There are two kinds of trendlines: up and down.

Figure 2. 6: Up and Down Trendline



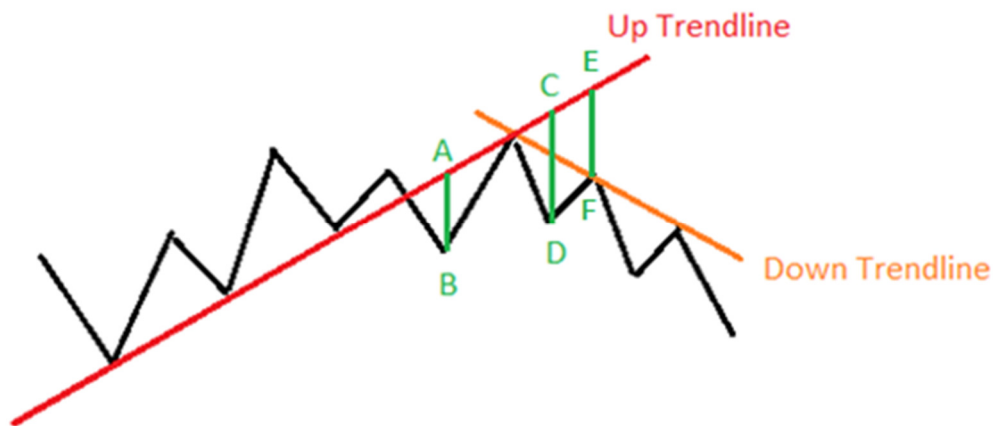
Source: Murphy, 1999, p.65-66, Figure 4.6a and 4.6b

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An up trendline is a straight line that links all the troughs in an uptrend, while a downtrend is a straight line that connects all the peaks in a downtrend. Chartists usually use two troughs or two peaks to draw up or down trends, and use the third trough or peak to confirm the direction and the slope of the trend. Please see the above image for details. Once the direction and the slope of the trend are confirmed, it assumes that the slope of the trend will always maintain the same. If the stock price is below the trendline in an uptrend, it shows a breakage of the trendline and indicates a direction change of the trend. This also applies to a downtrend. Therefore, one of the functions of a trendline is to tell when the direction of the price movements is changing (Murphy, 1999).

The next question is how much below the up trendline, and how much higher than the down trendline are valid signals for indicating the breakage of an up trendline or down trendline. According to Murphy, 3% is the criterion for long-term trendlines.

Figure 2. 7: Indicating the Breakage of an Up Trendline



For instance, in the above Figure 2.7, the red trendline is a long-term up trendline. If the price on the up trendline at point C is \$100, and the actual price at point D is \$96, since the actual price is 4% below the up trendline, the actual price shows a breakage of the

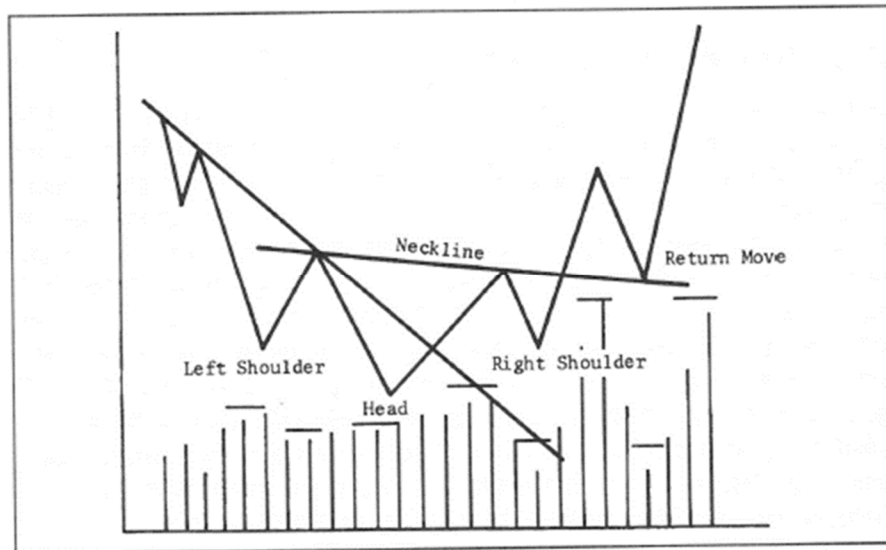
trendline and indicates a possible direction change of the up trendline. Time is also used to confirm the breakage of the trendlines. Usually, two-day successive violation of the 3% rule implies a breaking trendline. On the same image, point D and point F are the two-day successive violations of the 3% rule of point C and point E, so the direction of the up trendline has been indicating a change to down trendline. Murphy comments that the 3% criterion and the two-day rule also could be utilized for judging violation of support and resistance levels. When the trendlines change direction and slope, punctuations appear. Otherwise, according to Newton's first law, the direction and the slope of the trendline should remain the same.

Chart Pattern Analysis:

Edwards, Magee, and Bassetti stated that the principal method for technical analysis is charting (2013). Charts could be classified into different categories or patterns. Generally speaking, there are two types of patterns: reversal and continuation (Edwards et al., 2013; Murphy, 1999). As their names imply, reversal means the pattern will reverse once the pattern finishes the entire shape, while continuation means the trend will continue, even though a minor correction could occur (Edwards et al., 2013; Murphy, 1999). Another difference between reversal patterns and continuation patterns is their duration. Reversal patterns always take a longer time to form and reflect major trend changes, while the continuation patterns usually take a shorter time to form and represent intermediate term (Edwards et al., 2013; Murphy, 1999). According to Murphy, price patterns have the predictive value (1999). If the charts fit reversal patterns, the future direction will change from the previous trend. For instance, before the reversal pattern,

Figure 2.8 below shows a downtrend, and after the formation of the reversal pattern, the direction of the trend has changed to an uptrend.

Figure 2. 8: Reversal Pattern

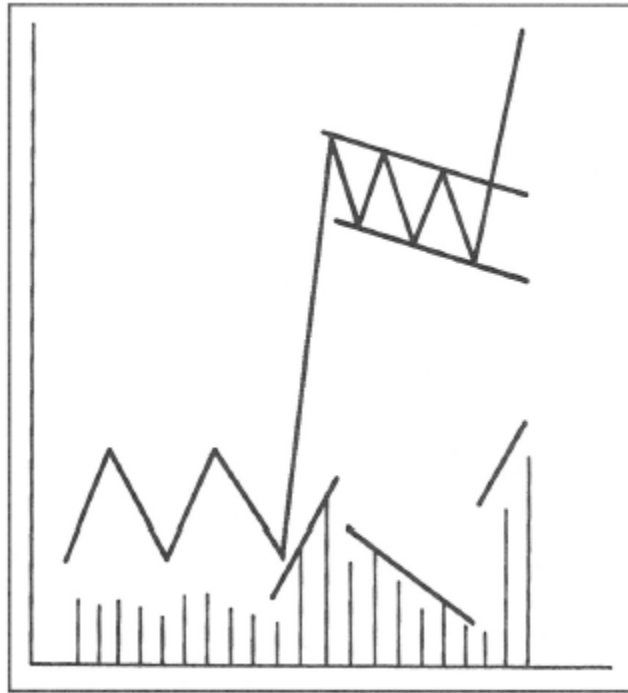


Source: Murphy, 1999, p.110, Figure 5.2a

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If the charts fit continuation patterns, the direction of the trend will not be changed; for instance, prior to continuation pattern, there is an uptrend, and after the formation of the continuation pattern, the direction of the trend still keeps uptrend. Please see Figure 2.9 below for details.

Figure 2. 9: Continuation Pattern



Source: Murphy, 1999, p.142, Figure 6.6a

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Murphy (1999) also stated some preliminary points common to all reversal patterns. These preliminary points might be useful for studying revenue punctuations. The *first* one is a matter of logic: a prior trend must exist. The reversal refers to a reverse of the prior trend, so the prior trend must exist. *Second*, once reversal happens, the major trend line is broken. *Third*, there is a relationship between the height and the width of the price pattern. Height refers to the volatility of the pattern, and the width is the amount of time for forming the whole pattern. Murphy argues that if the pattern is more volatile, it takes longer time to build the pattern.

There are nine major reversal and continuous patterns for the chart pattern analysis. However, they are not closely related to the research focused on in this dissertation, so they are not discussed here.

Technical analysis studies the trend and chart patterns. Trend analysis focuses on the uptrend, downtrend, sideways, resistance, support, up trendline, and down trendline. When uptrend changes to downtrend, or downtrend changes to uptrend, or up trendline changes to down trendline, or vice versa, punctuations appear. Murphy commented that the 3% criterion and two-day successive rule could be utilized for judging the breakage of trendlines. In other words, in trend analysis, the 3% criterion and two-day successive rule could be used to study punctuations. The revenue punctuations might have the similar criterion and rule, and this research could test the revenue data to verify whether revenue punctuations have the similar criterion and rules.

Chart pattern analysis focuses on the continuous patterns as well as the reversal patterns. The techniques for studying continuation and reversal patterns might be utilized for studying revenue punctuations, because no other methods serve this purpose. As Murphy stated the height of the price pattern is related to the width of the price pattern (Murphy, p.102). This might be true with revenue punctuations. The height of the price pattern could be the severity of revenue punctuation and the width of the pattern could be the duration of the revenue punctuation. This research employs technical analysis in testing whether there is a relationship between the severity and duration of revenue punctuations.

CHAPTER 3

METHODS

3.1 Philosophical Foundations

The main research question for this study is whether there is a relationship between the severity and duration of revenue punctuations, a very different problem than prior research has identified, much less studied. Previous research and studies concentrated on demonstrating the existences of tax revenue punctuations and exploring what factors may trigger them. However, the pattern of tax revenue punctuations is not well studied. The pattern of tax revenue punctuations is similar to the price change patterns in the stock market; both display the changes in dollar amount over time. Since technical analysis is one of the two main methods used for stock market analysis, this research examines whether technical analysis could also be utilized in studying the pattern of tax revenue punctuations.

According to Murphy (1999), there are three premises that technical analysis is built on. Before testing whether technical analysis could be used for this research, it is legitimate to prove that tax revenue meets the premises of technical analysis. As long as tax revenue meets the three premises, it is valid to use technical analysis for studying tax revenue punctuations.

The *first* premise is that “market action discounts everything” (Murphy, 1999, p.2). This premise means that even though the stock market is affected by all kinds of factors including economy, politics, investors’ behaviors and so forth, these factors are all reflected by the price changes in the stock market. This is also true for tax revenue. All the factors such as economics, politics, policies, and taxpayers’ behavior that affect tax

revenue collections are all reflected in the total tax revenue collections. In addition, tax policy changes to the tax collection base as well as tax rates that forecasters need to concern are also reflected in the total revenue collections. Therefore, tax revenue meets the first premise of technical analysis.

The *second* premise is “price moves in trend,” which means “a trend in motion will continue in the same direction until it reverses” (Murphy, 1999, p.4). This also applies to tax revenue. Supported not only by Newton’s first law (Murphy, 1999), but also Baumgartner and Jones’ punctuated equilibrium theory (Baumgartner & Jones, 2009), the tax revenue trend will continue until punctuations happen, at which time the direction of the trend might change. Thus, tax revenue meets the second premise.

The *third* premise is “history repeats itself” (Murphy, 1999, p.4). Murphy argues that people always learn from past experiences, past experiences direct future behaviors. As such, history repeats itself. This is also true for tax revenue. Most of the tax rates and tax policies are generated based on the past experiences, and most of the time they are unchanged year after year. Thus, past experiences in tax revenue could predict future behaviors. Additionally, Norbert Wiener (1961) also reported that using past experience could project future in statistics. Wiener stated (1961):

We can compute the amount of information concerning any statistical parameter or set of statistical parameters, which fixing of the past will give us. We can even compute the whole amount of information which a knowledge of the past will give us of the whole future beyond a certain point; although when this point is the present, we shall in general know the latter from the past. (p. 69)

Therefore, tax revenue meets the third premise and tax revenue history repeats itself.

In summary, the characteristics of tax revenue changes are very similar to those of stock price movements, and tax revenue meets the above three premises of technical analysis. Therefore, technical analysis is a valid method for studying tax revenue punctuations.

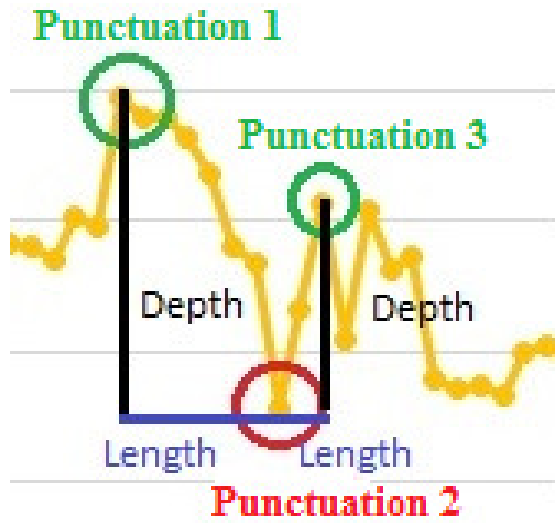
This research mainly studies two questions related to the pattern of tax revenue punctuations. The first question comes from Murphy's 3% rule (1999), which he utilized to judge the punctuation of trendlines. The tax revenue punctuations might have a similar criterion. Therefore, this research searches for such a rule. The question is as below:

1. Is there a criterion to judge occurrences of tax revenue punctuations?

Research question #2 is developed from Murphy's preliminary points (1999) to all reversal patterns. He comments that there is a relationship between height and width of the price pattern (Murphy, 1999 p.102). Height is the volatility of the pattern and width is the amount of time for building the whole pattern. In this research, depth refers to the height in Murphy's book, which represents the severity of tax revenue punctuations. Depth for revenue punctuations in this research is defined as the changes in dollar amount from one tax revenue punctuation to another punctuation. Here, the length refers to the width of Murphy's price pattern, which represents the duration of the revenue punctuations. Length for tax revenue punctuations in this research is defined as the period of time between one tax revenue punctuation and another punctuation. Below is research question #2, and Figure 3.1 demos the depth and length of this study.

2. Is there a relationship between depth and length of revenue punctuations?

Figure 3. 1: Depth and Length



If there is a relationship between the lengths and depths of revenue punctuations, I conclude that tax revenue punctuations follow a pattern, which is the relationship between the severity and duration of tax revenue punctuations. If there is no relationship between them, I claim that the relationship of the length and depth of tax revenue punctuations may not exist, but I could not conclude that tax revenue punctuations do not follow a pattern. The tax revenue punctuations may follow other patterns that are unknown.

3.2 Data

There are twenty-five tax categories across all fifty states in the U.S. Table 3.1 below displays the tax categories by the sequence of tax codes. It also contains the numbers of states having these tax categories.

Table 3. 1: Tax Categories for All the Fifty States in the U.S

Tax Categories	Numbers of State Having this Tax
T01 Property Taxes	39
T09 General Sales and Gross Receipts Taxes	45
T10 Alcoholic Beverages	50
T11 Amusements-Sales and Gross Receipts	40
T12 Insurance Premiums	50
T13 Motor Fuels	50
T14 Pari-mutuels	38
T15 Public Utilities Sales Tax	44
T16 Tobacco Products	50
T19 Other Selective Sales and Gross Receipts Taxes	50
T20 Alcoholic Beverages License	47
T21 Amusements-License Taxes	44
T22 Corporations in General	49
T23 Hunting and Fishing	50
T24 Motor Vehicles	50
T25 Motor Vehicle Operators	49
T27 Public Utilities-Licenses	35
T28 Occupation and Businesses, NEC	50
T29 Other License Taxes	49
T40 Individual Income Taxes	43
T41 Corporation Net Income Taxes	46
T50 Death and Gift Taxes	50
T51 Documentary and Stock Transfer Taxes	35
T53 Severance Taxes	34
T99 Other Taxes, NEC	26

Table 3.2 below reports the proportion of total tax collections by tax categories in descending order. I limited this research to the top five tax categories. The categories are Individual Income Tax (Tax code 40), General Sales and Gross Receipts Taxes (Tax code 09), Corporation Net Income Tax (Tax code 41), Motor Fuels Tax (Tax code 13), and Motor Vehicles Tax (Tax code 24). These five categories accounted for 80% of the total tax collections.

Table 3. 2: The Percentages of Total Tax Collections

Tax Categories	Percentage of Total Tax Collection
T40 Individual Income Taxes	34.85%
T09 General Sales and Gross Receipts Taxes	33.18%
T41 Corporation Net Income Taxes	6.65%
T13 Motor Fuels	5.87%
T24 Motor Vehicles	3.10%
T19 Other Selective Sales and Gross Receipts Taxes	2.17%
T16 Tobacco Products	2.05%
T12 Insurance Premiums	1.73%
T15 Public Utilities Sales Tax	1.52%
T01 Property Taxes	1.50%
T28 Occupation and Businesses, NEC	1.32%
T53 Severance Taxes	1.18%
T22 Corporations in General	1.04%
T10 Alcoholic Beverages	0.91%
T50 Death and Gift Taxes	0.75%
T51 Documentary and Stock Transfer Taxes	0.74%
T11 Amusements-Sales and Gross Receipts	0.61%
T25 Motor Vehicle Operators	0.24%
T23 Hunting and Fishing	0.16%
T29 Other License Taxes	0.10%
T99 Other Taxes, NEC	0.09%
T27 Public Utilities-Licenses	0.08%
T20 Alcoholic Beverages License	0.05%
T21 Amusements-License Taxes	0.05%
T14 Pari-mutuels	0.04%

The state tax revenue data are collected from the U.S Census Bureau “Quarterly Summary of State Tax Collections by State” dataset. These quarterly data are based on state and local tax revenues. The U.S Census Bureau released data ranging from 1962 to 2016. However, from 1966 to 1976, Corporation Net Income Tax was tabulated with Individual Income Tax. The Individual Income Tax and Corporation Net Income Tax are the two major targets of this study. The merged data from 1966 and 1976 could not be utilized to study the behaviors of the two major tax categories. Thus, this research covers all fifty states’ tax revenue from 1977 to 2016, which encompasses 40 years and 160 quarters, but excludes information from 1966 to 1976. I made use of the complete data.

3.3 Missing Data

The U.S Census Bureau's "Quarterly Summary of State Tax Collections by State" dataset is the most suitable dataset for this study since it provides the quarterly tax revenue collections by states and by tax categories. However, it has missing data issues. Missing data is important since it impacts the accuracy of data analysis. For instances, it can "reduce the statistical power of a study and produce biased estimates, leading to invalid conclusions" (Kang, 2013, p. 1). Thus, I could not ignore the missing data issues in this study.

There are two kinds of missing data issues of the dataset studied in this research. The first kind is information was not available for the 4th quarter of 1992 through the 4th quarter of 1993 for all the states and all the tax categories. In other words, General Sales and Gross Receipts Taxes miss 225 data points (5 quarters*45 states), Corporation Net Income Tax misses 230 data points (5 quarters*46 states), Individual Income Tax misses 215 data points (5 quarters*43 states), Motor Fuels Tax misses 250 data points (5 quarters*50 states), and Motor Vehicles Tax misses 250 data points (5 quarters*50 states). There are a total of 1,170 data points missing.

The second missing data issue is that the collections of some tax categories for several states at some time were not available. The tax categories, states and time are all random. For example, the tax revenue of General Sales and Gross Receipts Taxes for Arizona in the 2nd quarter of 1980 is not available. This kind of missing values occupies a small percent of the total data points. Table 3.3 summarizes the numbers of missing values and the percentages of missing values out of the total data points.

Table 3. 3: Missing Values and Missing Value Rates

Tax Categories	Counts of Missing Value	Total Data Points	Missing Value Rate
General Sales and Gross Receipts Taxes	55	7,200	0.76%
Motor Fuels Tax	65	8,000	0.81%
Motor Vehicle Tax	67	8,000	0.84%
Individual Income Tax	45	7,040	0.64%
Corporation Net Income Tax	48	7,360	0.65%
Total	280	37,600	0.74%

Different missing value mechanisms require different treatments. According to Donald B. Rubin (1977), Alan C. Acock (2005), Steffen Moritz, Alexis Sardá, Thomas Bartz-Beielstein, Martin Zaefferer and Jörg Stork (2015), there are three major mechanisms leading to missing values: missing at completed random (MCAR), missing at random (MAR), and nonignorable missing (NI). Generally speaking, each mechanism of missing values has a specific treatment. Thus, three treatments are mainly used for missing value issues.

The first major mechanism is missing at completed random (MCAR). Defined by the above scholars, MCAR refers to the missing values that have no relationship with the values of other variables in the dataset. In other words, the data is entirely missing at random. The dataset in this study is univariate time-series data. Because I study each tax category by states for research question #1, it is time-series data. According to Steffen Moritz, Alexis Sardá, Thomas Bartz-Beielstein, Martin Zaefferer and Jörg Stork (2015), as long as the missing values of univariate time-series dataset are independent of the point of time of the observation, they belong to MCAR mechanism. The second kind of missing values of this study are entirely random and have no relationship with the point of time. Thus, the second kind of missing values in this research belongs to MCAR.

The traditional approach for dealing with the first major mechanism - MCAR - in a large sample is list-wise or case deletion. In SAS software, all the missing values are

coded as single dots, considered as invalid data and not analyzed. Since the second kind of missing values in this research belongs to MCAR and occupies a tiny portion of total data points (all of them less than 1%), SAS's method is appropriate for data analysis of the second kind of missing value in this research.

The second major mechanism is MAR. It refers to “the missing values that are independent of the value of the observation itself. However, it is dependent on other variables” (Acock, 2005). Again, according to Steffen Moritz, Alexis Sardá, Thomas Bartz-Beielstein, Martin Zaefferer and Jörg Stork (2015), for univariate time-series data, if the missing values are dependent of the point in time of the observation, they belong to MAR. For the first kind of missing values in this study, all the missing values are in the period from the 4th quarter of 1992 to the 4th quarter of 1993. They are dependent on the point in time. Thus, the second kind of missing values of this study is MAR.

The traditional approach for dealing with the second major mechanism MAR is “mean substitution”. Acock commented that this approach assumes that missing values are normally distributed and there are no extreme values (2005). Based on the table below from National Bureau of Economic Research (2010), there is no economic crisis between the period of the first kind missing values (MAR), and there is no sudden tax policy changes either. This suggests that mean substitution is an appropriate method for the imputation of the first kind missing values in this study.

Figure 3. 2: U.S Business Cycle Expansions and Contractions from 1980 to 2009

<u>BUSINESS CYCLE REFERENCE DATES</u>		<u>DURATION IN MONTHS</u>			
Peak	Trough	Contraction	Expansion	Cycle	
<i>Quarterly dates are in parentheses</i>		<i>Peak to Trough</i>	<i>Previous trough to this peak</i>	<i>Trough from Previous Trough</i>	<i>Peak from Previous Peak</i>
January 1980(I)	July 1980 (III)	6	58	64	74
July 1981(III)	November 1982 (IV)	16	12	28	18
July 1990(III)	March 1991(I)	8	92	100	108
March 2001(I)	November 2001 (IV)	8	120	128	128
December 2007 (IV)	June 2009 (II)	18	73	91	81

Source: National Bureau of Economic Research, 2010

Since the nonignorable missing (NI) is not the mechanism of missing data in this research, it is not described here.

Because of different sizes and mechanisms of missing values, the two kinds of missing values of this research calls for two different methods. The first kind of missing values (MAR) occupies a significant portion of the total data points, and the data points are missed by the pattern from the 4th quarter of 1992 to the 4th quarter of 1993, so mean substitution method is utilized to deal with this kind of missing values. The second kind of missing values (MACR) is entirely random missed and it occupies a very small fraction of all the data points, so list-wise or case deletion method is used to manage the data points.

3.4 Research Design

Tax revenue punctuations are similar to outliers in statistics. As identified in literature review chapter, outliers are the data points that significantly differ from the majority of the data points. Tax revenue punctuations also reflect the revenue changes that are dramatically different from other incremental revenue changes. Due to lack of

research on tax revenue punctuations, it is hard to tell what size constitutes an incremental change or is considered a dramatic revenue change. Because of the similarities between outliers and revenue punctuations, this research is designed to apply the statistical techniques of diagnosing outliers to tax revenue punctuation analysis.

In statistics, a studentized residual is commonly used for identifying outliers of dependent variable (Y variable) in regression analysis. It is defined as an ordinary residual divided by an estimate of its standard deviation (Stevens, 1984):

$$r_i = \frac{\hat{e}_i}{\hat{\delta} \sqrt{1-h_{ii}}} \quad (3.1)$$

Where $\hat{e}_i$ is the estimated ordinary residual for each data point, which is the difference between the observed and predicted dependent variable. $\hat{\delta}$ is the estimated standard deviation, which is the square root of the average of the squared differences from the Mean. h_{ii} is leverage points. With SAS software, studentized residuals for each data point could be computed. If the absolute studentized residuals are larger than the critical value of the desired probability, the data points are identified as outliers.

Research question # 1 is related to exploring the criterion for judging the appearance of tax revenue punctuations. Inspired by the statistic method of identifying outliers, studentized residuals could also be used to judge the appearance of tax revenue punctuations. Due to the various features of the fifty U.S. states, such as different tax policies, demographics, population, and economy, and the magnitudes and patterns of tax collections, this research calculates the studentized residuals for each data point by states and by tax categories. If the absolute studentized residuals are larger than its critical value of the desired probability p , the data points could be identified as tax revenue punctuation

points. The most desired probability in statistical analysis is 95%. Thus the probability used for this research is 95%, and the critical value for 95% probability is 1.96.

Once all the tax revenue punctuation points are noted, research question #2 could be answered. Inspired by Murphy's comment on technical analysis of stock market data that the height of the price pattern is related to the width of the price pattern, the research question #2 tests whether the depth of revenue punctuations has a relationship with the length of them. Since tax revenue punctuation points have been noted in the research question #1, depth and length of revenue punctuations could be computed. As mentioned in the philosophical foundation section of this chapter, especially that surrounding Figure 3.1, the depths of tax revenue punctuations are the changes in dollar amount between the tax revenue punctuation points, and the length is the numbers of quarters between the tax revenue punctuation points. After the depths and lengths of each state collected, with simple linear regression, the relationship between the depths and lengths of a tax category in each state could be identified, and research question #2 has an answer. Since positive and negative revenue punctuations have different patterns, the relationships between positive and negative revenue punctuations are studied separately. The linear regression is denoted as below:

$$Y_{depth} = \beta_0 + \beta_1 X_{length} + \varepsilon \quad (3.2)$$

3.5 Procedures for Data Analysis

To answer the two research questions, six steps in total are needed to follow (two steps for research question #1 and four steps for research question #2). Since this study employs the same methods for each of the fifty states and each of the five tax categories, the steps below only use the General Sales and Gross Receipts Taxes (also called sales

tax in this dissertation) of Alabama as an example to demonstrate the specific procedures that used to answer the research questions. For the states that do not have one of the five tax categories, the number of total states for that tax category is less than 50.

Research question #1: Is there a criterion to judge the appearance of revenue punctuations?

Step 1: Use SAS software to run a fitted regression model for the General Sales and Gross Receipts Taxes of Alabama. The dependent variable is the General Sales and Gross Receipts Taxes, and the independent variables are the numerical sequence for all the quarters from 1977 quarter 1 to 2016 quarter 4 (showing as 1,2,3,4,5,6...160), and the seasonal adjustment factor for quarters. Please see the equation 3.3 for details.

$$Y_{\text{Sales Taxes}} = \beta_0 + \beta_1 X_{\text{quarters}} + \beta_2 Q_1 + \beta_3 Q_2 + \beta_4 Q_3 + \varepsilon \quad (3.3)$$

The results calculated by SAS also include studentized residuals for each data point for the General Sales and Gross Receipts Taxes of Alabama.

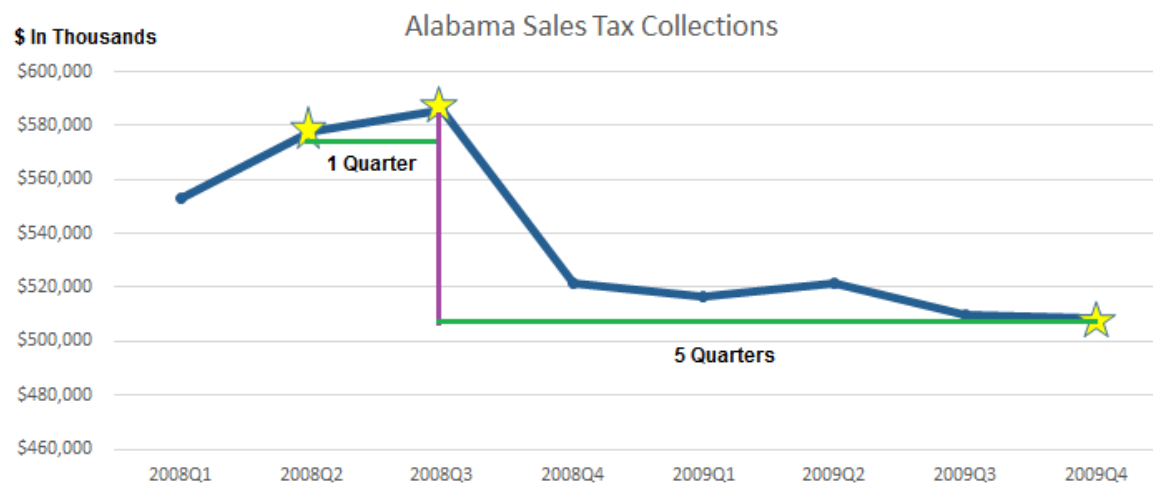
Step 2: Compare the studentized residuals with the critical value of desired 95% probability, which is 1.96 for positive values and -1.96 for negative values. If the studentized residuals are equal or larger than 1.96, or if the studentized residuals equal or smaller than -1.96, the data points are marked as “1” in a new column, which indicate revenue punctuations (outliers). If the studentized residuals are less than 1.96 or larger than -1.96, the data points in the new column are marked as “0”. In other words, the newly created column shows whether a data point is a revenue punctuation point or not. Thus, research question #1 is answered. The criterion for judging occurrences of tax revenue punctuations is to compare the calculated studentized residuals with critical

values. If the studentized residuals are out of the range of critical values, the studentized residuals associated with data points are identified as revenue punctuation points.

Research Question #2: Is there a relationship between the depth and length of revenue punctuations?

Step 1: Count the time periods between revenue punctuation points. In other words, count the total quarters between every “1” of the newly created column discussed in research question #1 step 2. For instance, in the State of Alabama from the 1st quarter of 2008 to the 4th quarter of 2009, three data points are marked as “1”, which are the 2nd quarter of 2008, 3rd quarter of 2008, and 4th quarter of 2009. These three quarters indicate that tax revenue has punctuations during these time periods. From 2008 quarter 2 to 2008 quarter 3, it takes only one quarter, so the length of these two revenue punctuations is 1. The time periods from 2008 quarter 3 to 2009 quarter 4 are five quarters, so the length is 5. Figure 3.3 below displays the details.

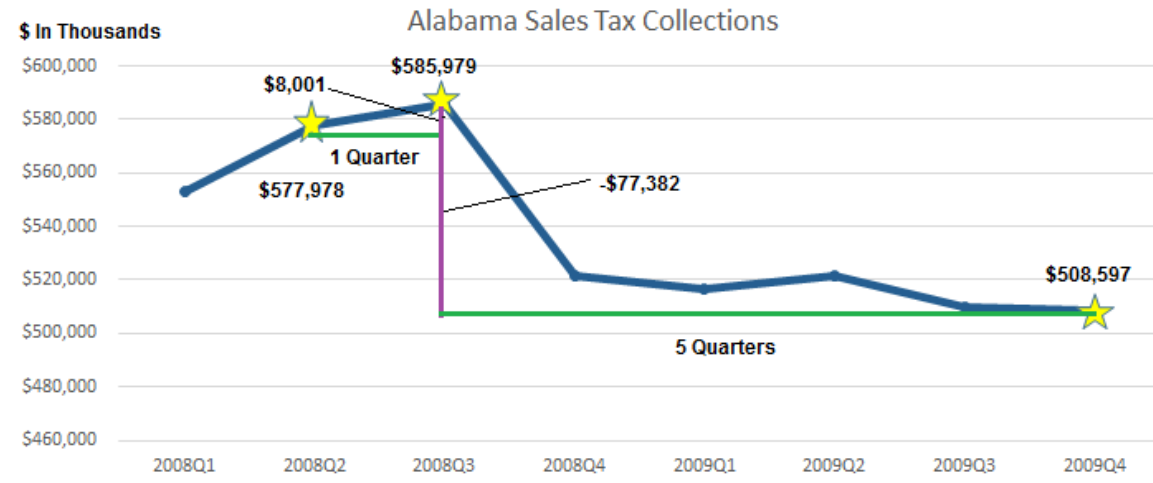
Figure 3. 3: The Lengths of Alabama Sales Tax Revenue Punctuations from 2008 to 2009



Step 2: Calculate the amount changes between tax revenue punctuations. In other words, calculate the growth amounts between “1s” of the newly created column

discussed in research question #1 step 2. Using the example of Alabama from the 1st quarter of 2008 to the 4th quarter of 2009, the tax revenue punctuation points are the 2nd quarter of 2008, 3rd quarter of 2008, and 4th quarter of 2009. The tax collections for these three quarters are \$577,978,000, \$585,979,000 and 508,597,000. The growth amount from 2008 quarter 2 to 2008 quarter 3 is \$8,001,000, and the growth amount from 2008 quarter 3 to 2009 quarter 4 is -\$77,382,000. The details are displayed in Figure 3.4 below.

Figure 3. 4: The Depths of Alabama Sales Tax Revenue Punctuations from 2008 to 2009



Step 3: Create a new column called “Sign” to record whether the punctuation is an increase one or a decrease one. If the amount change is positive, in the “Sign” column, enter “1”; if the amount change is negative, in the “Sign” column, key in “-1”.

Step 4: Use simple regression to analyze the relationship between depths and lengths for positive and negative punctuations of each state by tax category separately. For instance, there are 12 punctuated data points for Alabama sales tax collections. Out of these 12 punctuations, seven are positive, and five are negative. Table 3.4 and 3.5 below demonstrate the positive and negative punctuations respectively. Sign column indicates

whether the data points have positive or negative punctuations. “1” refers to positive punctuations and “-1” refers to negative punctuations.

Table 3. 4: The Lengths and Depths for Positive Punctuated Sales Tax of Alabama

State	Lengt	Dep	Sign
Alabama	115	442,772	1
Alabama	1	25,020	1
Alabama	1	11,252	1
Alabama	1	19,725	1
Alabama	1	7,556	1
Alabama	2	7,472	1
Alabama	1	8,001	1

Table 3. 5: The Lengths and Depths for Negative Punctuated Sales Tax of Alabama

State	Lengt	Dep	Sign
Alabama	1	(13,854)	-1
Alabama	1	(5,868)	-1
Alabama	1	(9,235)	-1
Alabama	1	(18,814)	-1
Alabama	5	(77,382)	-1

With the positive punctuated and negative punctuated data for Alabama sales tax collections, after applying the regression analysis for positive and negative punctuations separately, coefficient β_1 shown on formula 3.4 below is known. If the coefficient β_1 is statistically significant, it could convey the relationship between depths and lengths. Thus research question #2 is answered.

$$Y_{depth} = \beta_0 + \beta_1 X_{length} + \varepsilon \quad (3.4)$$

This chapter includes five sections. The first section discusses the philosophical foundations of the research methods, which provides solid support for the methods of this research. The second section is mainly related to the data used in this research, so the readers know what kind of data I am studying. The third section discloses the missing

data issue in this research and explains how I handle it. The fourth section is about research design for each question raised in this dissertation and how to answer it at a high level. The last section displays the step-by-step procedures for data analysis, so researchers or practitioners could follow these steps to conduct their own research with a different scope, like studying the federal tax and revenues during exceptional time.

CHAPTER 4

RESULTS AND FINDINGS

This research focuses on state government revenue punctuations in the United States. The results reported in this chapter reveal revenue punctuations of the five significant state taxes over the period from 1977 to 2016. Beyond identifying revenue punctuations, I report the statistical relationships between their depths and lengths. This chapter consists of three sections. The first two sections discuss the results and findings of the research questions that guide this project. In the third section, I present a case study about the State of Arizona's sales taxes and their punctuations to demonstrate how forecasters can use the findings of this research.

4.1 What Are Punctuations and Do They Exist in State Revenue Collections?

Revenue punctuations are the revenue collections exceeding the expected highs or lows for a period. Research question #1 asks whether there are revenue punctuations in state revenue collections and how to identify them. The result of research question #1 provides a rule to determine cases that exceed the norm thereby identifying revenue punctuations. I make use of a body of statistics that addresses outliers under the normal distribution to answer research question #1 for the five tax categories. The method relies on the ability to compute the studentized residuals following a model that regresses taxes on quarters. The resulting model allows a measure between the observed tax collections and its predicted values (Appendix A shows the results of regression coefficients used to calculate the predicted values). Under such a model the studentized residuals follow a t-distribution. As such when I have a studentized residual that exceeds two standard errors, I declare the actual collections as punctuated revenues.

The fit of these regression models reveals that except in the case of Motor Fuels Tax in the state of Tennessee, the five tax categories for each state in this research contain positive, negative or both positive and negative revenue punctuations (Appendix B displays two-dimensional frequency tables for counts of states by punctuation and by tax category). Three taxes on sales, motor fuels and motor vehicle for some state do not have both positive and negative revenue punctuations.

Consider the few states that do not have punctuations in one or more taxes. For sales tax collections, five states including Colorado, Minnesota, Missouri, Nebraska, and Tennessee do not have negative revenue punctuations (Table 4.1).

Table 4. 1: States Do Not Have Negative Sales Tax Punctuations

State	# Of Positive Punctuations	# Of Negative Punctuations	# of Total Punctuations
Colorado	2	0	2
Minnesota	3	0	3
Missouri	3	0	3
Nebraska	3	0	3
Tennessee	5	0	5

For motor fuels tax collections, four states including Illinois, Massachusetts, New York, and Rhode Island do not have negative revenue punctuations. Only the state of Kansas does not have positive revenue punctuations, but the state of Tennessee does not have either positive or negative revenue punctuations (Table 4.2).

Table 4. 2: States Do Not Have Positive and Negative Motor Fuels Tax Punctuations

State	# Of Positive Punctuations	# Of Negative Punctuations	# of Total Punctuations
Illinois	2	0	2
Kansas	0	3	3
Massachusetts	3	0	3
New York	1	0	1
Rhode Island	2	0	2
Tennessee	0	0	0

For motor vehicle tax collections, two states including Colorado and Georgia do not have negative revenue punctuations (Table 4.3).

Table 4. 3: States Do Not Have Negative Motor Vehicle Tax Punctuations

State	# Of Positive Punctuations	# Of Negative Punctuations	# of Total Punctuations
Colorado	3	0	3
Georgia	1	0	1

There are 13 states for these three tax categories (five states for Sales Tax, six states for Motor Fuels Tax, and two states for Motor Vehicle Tax) that do not have positive, negative, or both revenue punctuations. These states only occupy a small portion of the overall states and tax categories. Furthermore, except Motor Fuels Tax in Tennessee that does not have both positive and negative revenue punctuations, the other 12 states have either positive or negative revenue punctuations. The answer to research question #1 is that except Motor Fuels Tax in Tennessee, revenue punctuations exist in state tax revenue collections. This finding is supported by revenue punctuation modeled, and diagnostics test in the studentized residuals applied.

Beyond answering the research question #1, it is also interesting to find that among these five tax categories, individual income tax has the most positive revenue punctuations, and motor fuels tax has the least positive revenue punctuations. Corporate net income tax has the most negative revenue punctuations, and the state sales tax has the least negative revenue punctuations. Table 4.4 summarizes the total numbers of positive and negative revenue punctuations by tax category as well as the percentages out of the total data points for each tax category.

Table 4. 4: Total Counts and Percentage of Revenue Punctuations by Tax Category

Tax Category	# Of Positive Punctuations	% Of Positive Punctuations	# Of Negative Punctuations	% Of Negative Punctuations
State Sales Tax	242	3.4%	100	1.4%
Corporate Net Income Tax	232	3.2%	177	2.4%
Individual Income Tax	251	3.6%	113	1.6%
Motor Fuels Tax	198	2.5%	136	1.7%
Motor Vehicle Tax	230	2.9%	139	1.7%

4.2 Patterns of Revenue Punctuations

Research question #2 relies on the patterns of the revenue punctuations for each state and its tax category. Specifically, the question investigates whether there are relationships between the changes in dollar amount and the number quarters it takes from one revenue punctuation to another. The expected outcome to research question #2 is “Yes,” which means more dollar changes associated with the longer time it takes, or fewer dollar changes associated with the shorter time it takes. The question is explored through the fit of a linear regression model with the changes in dollars as the response, and the quarters it takes from one revenue punctuation to another as a covariate. I do this for all states, for each tax category while making note of positive and negative punctuations.

The analysis reveals that not all the states and all the tax categories have statistically significant relationships between the change in dollar amount and the number of quarters taken. There are 16 out of 45 states with statistically significant relationships as it pertains to positive sales tax revenue punctuations. There are 8 out of 40 states with statistically significant relationships as it pertains to negative sales tax revenue punctuations.

For Corporate Net Income Tax, there are 10 out of 46 states that have statistically significant relationships as it pertains to positive revenue punctuations, and 6 out of 46 states that have statistically significant relationships as it pertains to negative revenue punctuations.

For Individual Income Tax, there are 16 out of 43 states that have statistically significant relationships as it pertains to positive revenue punctuations, and there are 4 out of 43 states that have statistically significant relationships as it pertains to negative revenue punctuations.

For Motor Fuels Tax, there are 15 out of 48 states that have statistically significant relationships as it pertains to positive revenue punctuations, and there are 7 out of 45 states that have statistically significant relationships as it pertains to negative revenue punctuations.

For Motor Vehicle Tax, there are 13 out of 50 states that have statistically significant relationships as it pertains to positive revenue punctuations, and there are 3 out of 48 states that have statistically significant relationships as it pertains to negative revenue punctuations.

I summarize the results in a contingency table, Table 4.5. It provides a cross-classification of tax category by the relationships of depth and length for revenue punctuations (“Yes” vs. “No”). “Yes” identifies the column counts the number of states with statistically significant relationships between depth and length of revenue punctuation, “No” column counts the number of states that do not have, and the total column sums both “Yes” and “No” columns.

Table 4. 5: Counts for Statistically Significant or Insignificant Relationships between Depth and Length of Revenue Punctuations

Tax Categories	Relationships between Depth and Length	Yes	No	Total
Sales Tax	Positive Punctuation	16	29	45
	Negative Punctuation	8	32	40
Corporate Net Income Tax	Positive Punctuation	10	36	46
	Negative Punctuation	6	40	46
Individual Income Tax	Positive Punctuation	16	27	43
	Negative Punctuation	4	39	43
Motor Fuels Tax	Positive Punctuation	15	33	48
	Negative Punctuation	7	38	45
Motor Vehicle Tax	Positive Punctuation	13	37	50
	Negative Punctuation	3	45	48

Table 4.6 through Table 4.10 exhibit the states that have statistically significant relationships between depth and length of positive and negative revenue punctuations for each tax category. These tables have a similar structure. The states are listed alphabetically. The upper section is for positive revenue punctuations, and the bottom section is for negative revenue punctuations. The first column (“State”) lists the state, the second column (“Prob”) gives the probability of no relationship between the depth and length of revenue punctuations. In this study, a probability less than 0.05, suggests that the state is considered to have a statistically significant relationship between depth and length of revenue punctuations. The third column (“Adj R Square”) represents the percentage of the variance in dollar amount changes explained by the number of quarters. The last three columns (“LowerCL,” “Estimate,” and “UpperCL”) display the lower confidence bound, estimated mean value and higher confidence bound for changes in dollar amounts from one quarter to another when positive or negative revenue

punctuation happens. The details of each table are explained in the next several paragraphs.

Table 4.6 displays how much sales tax a state could be changed from one quarter to another quarter when revenue punctuation happens. For positive sales tax punctuations, the State of Florida has the most significant variation from one quarter to another when punctuations happen, and the State of Idaho has the smallest. For negative revenue punctuations, although the relationships of New Jersey and Virginia are statistically significant, the results indicate an opposite direction and could not be used to forecast negative revenue punctuations. Exclude the states of New Jersey and Virginia, Illinois has the largest dollar changes and North Dakota has the least.

Table 4. 6: States with Statistically Significant Relationships between Depth and Length of Sales Tax Revenue Punctuations

Positive Revenue Punctuations					
State	Probt	Adj R Square	LowerCL	Estimate	UpperCL
Alabama	0.000	0.9975	3,574.21	3,773.15	3,972.09
Arizona	0.005	0.9999	10,900.21	12,009.78	13,119.34
Florida	0.000	0.9811	34,670.74	41,872.82	49,074.90
Georgia	0.032	0.9055	2,217.42	10,511.80	18,806.18
Idaho	0.000	0.9868	1,996.18	2,330.42	2,664.66
Illinois	0.000	0.9531	10,378.40	13,044.21	15,710.01
Indiana	0.010	0.7165	4,715.31	13,074.52	21,433.72
Kansas	0.042	0.7281	234.84	3,355.18	6,475.53
Kentucky	0.000	0.9991	5,344.49	5,616.50	5,888.51
New York	0.029	0.5050	1,827.19	12,830.51	23,833.82
North Carolina	0.002	0.8411	4,112.33	7,464.83	10,817.33
Ohio	0.000	0.8006	10,950.54	17,615.95	24,281.35
Oklahoma	0.003	0.8240	4,437.86	8,480.03	12,522.19
Tennessee	0.000	0.9988	11,018.66	11,667.42	12,316.19
Virginia	0.045	0.4326	147.25	5,270.33	10,393.41
West Virginia	0.034	0.6453	685.05	5,424.23	10,163.40
Negative Revenue Punctuations					
State	Probt	Adj R Square	LowerCL	Estimate	UpperCL
Alabama	0.002	0.9640	(21,368.10)	(16,359.81)	(11,351.53)
Arizona	0.004	0.9886	(31,934.74)	(25,222.17)	(18,509.60)
California	0.008	0.9997	(79,857.65)	(69,080.43)	(58,303.22)
Illinois	0.028	0.9178	(120,952.76)	(69,806.33)	(18,659.91)
New Jersey	0.024	0.6984	7,214.43	33,221.63	59,228.84
North Dakota	0.000	0.9995	(11,399.77)	(11,023.69)	(10,647.61)
Ohio	0.005	0.9341	(43,652.58)	(30,760.75)	(17,868.92)
Virginia	0.008	0.9997	158,477.70	189,679.25	220,880.80

Table 4.7 displays how much corporate net income tax a state could be changed from one quarter to another quarter when revenue punctuation happens. For positive corporate net income tax punctuations, the State of Tennessee has the largest amount variation from one quarter to another, and the State of Georgia has the smallest. For negative revenue punctuations, although the relationships of North Dakota and Vermont are statistically significant, the results indicate an opposite direction and could not be used to forecast negative revenue punctuations. Excluding the States of North Dakota and Vermont, the State of New Mexico has the largest dollar changes and the State of Rhode Island has the least based on the lower confidence bound.

Table 4. 7: States with Statistically Significant Relationships between Depth and Length of Corporate Net Income Tax Revenue Punctuations

Positive Revenue Punctuations					
State	Probt	Adj R Square	LowerCL	Estimate	UpperCL
Arkansas	0.013	0.7758	412.46	1,175.36	1,938.27
Connecticut	0.048	0.5813	173.15	11,734.58	23,296.01
Georgia	0.020	0.9980	89.61	150.23	210.85
Idaho	0.012	0.8803	3,616.76	8,552.26	13,487.75
Maine	0.046	0.4972	21.71	913.67	1,805.64
Nebraska	0.013	0.7747	1,836.24	5,261.04	8,685.83
New Mexico	0.030	0.7815	175.91	943.18	1,710.45
Ohio	0.000	0.9070	5,865.36	8,307.58	10,749.80
Tennessee	0.000	0.9889	35,700.63	41,114.83	46,529.02
West Virginia	0.018	0.8404	294.67	913.92	1,533.17
Negative Revenue Punctuations					
State	Probt	Adj R Square	LowerCL	Estimate	UpperCL
New Mexico	0.049	0.8561	(30,568.53)	(15,353.26)	(138.00)
North Dakota	0.040	0.8813	4,120.35	38,076.17	72,031.98
Ohio	0.007	0.8344	(28,701.44)	(18,606.31)	(8,511.18)
Rhode Island	0.002	0.9943	(721.04)	(606.62)	(492.19)
Vermont	0.032	0.9951	61.29	165.94	270.59
West Virginia	0.000	0.8952	(11,752.62)	(8,945.05)	(6,137.48)

Table 4.8 displays how much individual income tax a state could be changed from one quarter to another quarter when revenue punctuation happens. For positive individual

income tax punctuations, the State of California has the largest amount variation from one quarter to another, and the State of Tennessee has the smallest. For negative revenue punctuations, only the result for the State of Montana could be used to forecast negative revenue punctuations. The results of the remaining three states indicate an opposite direction and could not be utilized.

Table 4. 8: States with Statistically Significant Relationships between Depth and Length of Individual Income Tax Revenue Punctuations

Positive Revenue Punctuations					
State	Probt	Adj R Square	LowerCL	Estimate	UpperCL
California	0.003	0.8814	86,117.26	156,446.39	226,775.53
Colorado	0.017	0.8489	10,760.20	31,364.98	51,969.76
Georgia	0.000	0.9854	16,489.29	19,418.08	22,346.88
Hawaii	0.044	0.7173	205.65	4,389.12	8,572.59
Illinois	0.011	0.9673	12,815.12	23,481.31	34,147.51
Kansas	0.000	0.9593	5,392.73	7,234.82	9,076.92
Louisiana	0.031	0.7751	973.20	5,642.97	10,312.73
Maine	0.001	0.9745	3,341.28	4,495.35	5,649.42
Mississippi	0.049	0.4207	145.27	18,273.81	36,402.36
New Hampshire	0.036	0.9937	787.89	2,783.26	4,778.63
Ohio	0.034	0.7595	3,111.22	22,538.42	41,965.62
Oklahoma	0.002	0.7401	4,703.54	9,131.00	13,558.46
Rhode Island	0.023	0.3307	465.36	2,838.98	5,212.61
Tennessee	0.000	0.8862	1,150.56	1,713.24	2,275.91
Virginia	0.043	0.6026	1,328.10	25,400.64	49,473.19
West Virginia	0.002	0.9653	2,789.27	3,985.59	5,181.91
Negative Revenue Punctuations					
State	Probt	Adj R Square	LowerCL	Estimate	UpperCL
Georgia	0.034	0.9942	345,515.73	1,093,307.50	1,841,099.27
Montana	0.004	0.9866	(73,404.45)	(56,950.11)	(40,495.78)
Oklahoma	0.016	0.9988	314,501.30	457,706.00	600,910.70
Virginia	0.013	0.9992	1,122,156.38	1,513,675.00	1,905,193.62

Table 4.9 displays how much motor fuels tax a state could be changed from one quarter to another quarter when revenue punctuation happens. For positive motor fuels tax punctuations, although the relationship of Utah is statistically significant, the results indicate an opposite direction and could not be used to forecast positive revenue

punctuations. Excluding the State of Utah, the State of Pennsylvania has the largest amount variation from one quarter to another, and the State of Vermont has the smallest. For negative motor fuels tax revenue punctuations, similar to positive punctuations, the relationships of Connecticut, New Jersey, and New Mexico are statistically significant. However, the results of these three states indicate an opposite direction and could not be used to forecast negative revenue punctuations. Excluding these three states, the State of Maryland has the largest dollar changes and the State of Oregon has the least.

Table 4. 9: States with Statistically Significant Relationships between Depth and Length of Motor Fuels Tax Revenue Punctuations

Positive Revenue Punctuations					
State	Probt	Adj R Square	LowerCL	Estimate	UpperCL
Alaska	0.006	0.9998	210.68	239.96	269.24
Arizona	0.036	0.3052	61.37	794.26	1,527.16
California	0.047	0.3321	61.89	4,284.12	8,506.35
Colorado	0.020	0.9403	479.21	1,258.39	2,037.57
Connecticut	0.034	0.7618	206.68	1,444.62	2,682.57
Florida	0.011	0.9994	5,324.17	6,786.11	8,248.06
Georgia	0.024	0.9971	1,071.50	2,082.52	3,093.54
Maine	0.011	0.9679	303.23	550.95	798.67
Mississippi	0.019	0.9435	555.47	1,396.26	2,237.05
Nevada	0.026	0.9224	368.08	1,270.94	2,173.79
Ohio	0.049	0.5788	40.40	3,928.12	7,815.84
Pennsylvania	0.021	0.9979	6,010.20	10,244.27	14,478.35
Utah	0.005	0.9864	(871.75)	(675.31)	(478.87)
Vermont	0.000	0.9468	143.75	191.04	238.33
Wisconsin	0.001	0.9964	1,805.90	2,124.61	2,443.32
Negative Revenue Punctuations					
State	Probt	Adj R Square	LowerCL	Estimate	UpperCL
Connecticut	0.003	0.9908	8,129.77	10,687.33	13,244.90
Maryland	0.035	0.8981	(125,283.77)	(68,782.06)	(12,280.35)
Michigan	0.009	0.9996	(23,385.60)	(19,904.70)	(16,423.80)
New Jersey	0.008	0.9761	18,232.56	29,766.56	41,300.55
New Mexico	0.000	0.9945	22,836.49	25,152.78	27,469.06
Oregon	0.018	0.8406	(4,044.45)	(2,411.73)	(779.02)
Wisconsin	0.000	0.9987	(6,541.47)	(5,999.79)	(5,458.11)

Table 4.10 displays how much motor vehicle tax a state could be changed from one quarter to another quarter when revenue punctuation happens. For positive motor vehicle tax punctuations, the State of California has the largest amount variation from one quarter to another, and the State of New Mexico has the smallest according to the upper confidence bound. For negative motor vehicle tax revenue punctuations, the State of Kansas has the largest dollar changes and the State of West Virginia has the least base on the lower confidence bound.

Table 4. 10: States with Statistically Significant Relationships between Depth and Length of Motor Vehicle Tax Revenue Punctuations

Positive Revenue Punctuations					
State	Probt	Adj R Square	LowerCL	Estimate	UpperCL
Arizona	0.006	0.8420	290.97	616.54	942.12
California	0.043	0.4432	274.36	6,035.38	11,796.40
Colorado	0.002	1.0000	727.04	759.87	792.70
Hawaii	0.008	0.8186	152.90	357.28	561.65
Illinois	0.028	0.9961	2,513.16	5,726.37	8,939.58
Iowa	0.000	0.9557	1,805.92	2,162.77	2,519.63
Kansas	0.000	0.9764	424.10	525.35	626.59
Maryland	0.023	0.5370	494.51	2,607.52	4,720.53
New Mexico	0.001	0.9501	266.09	371.09	476.10
New York	0.000	0.9698	5,887.79	7,534.60	9,181.40
North Dakota	0.001	0.9956	1,343.47	1,608.78	1,874.09
Tennessee	0.001	0.7160	196.24	351.61	506.99
Utah	0.000	0.9167	322.02	469.43	616.84
Negative Revenue Punctuations					
State	Probt	Adj R Square	LowerCL	Estimate	UpperCL
Kansas	0.035	0.9939	(7,786.24)	(4,576.14)	(1,366.04)
Mississippi	0.001	0.9799	(7,381.65)	(6,013.53)	(4,645.40)
West Virginia	-	1.0000	(4,885.41)	(4,871.81)	(4,858.20)

Table 4.5 summarized the total numbers of states that have statistically significant relationships between depth and length of revenue punctuations versus the total numbers of the states without the statistically significant relationships. Table 4.6 to Table 4.10 listed the states that have a valid relationship between depth and length of revenue

punctuations for all the five tax categories. Although not all the states and all the tax categories have valid relationships between depth and length of revenue punctuations, for the state it does, I claim that the changes in dollars are associated with the time it takes from one punctuation to another, and research question #2 is answered.

4.3 A Case Study for Usage of the Results of the Two Research Questions

Section 4.1 and 4.2 addressed the results of the two research questions. These sections did not provide information on how forecasters can use these findings. This section demonstrates the results as it pertains to Arizona's sales tax. I concentrate on providing information on how to interpret the results in the analysis and forecasting of state government tax revenues.

Consider the 1st quarter of 2017 tax revenue as provided by Census Bureau. It shows that the Arizona sales tax is \$1,635,747,000. The following steps would be required.

Step 1: Calculate the predicted sales tax for Arizona in the 1st quarter of 2017, and the studentized residuals for Arizona sales tax in the 1st quarter of 2017 based on the regression model for Arizona sales tax as shown in Appendix Table A.1 (numbers in thousands). The calculation is denoted in (4.1)¹, and the parameter estimates in Appendix Table A.1 for Arizona is circled below.

$$\hat{Y}_{\text{Sales Taxes AZ}} = 18,711 + 9,628.4X_{\text{quarters}} + 13,343.16Q_1 + 8,307.75Q_2 + 5990.94Q_3 \quad (4.1)$$

State	Intercept	Quarters	Q1	Q2	Q3
Alabama	88,190.63	3,511.02	(10,551.58)	3,711.84	(3,135.41)
Arizona	18,711.00	9,628.40	13,343.16	8,307.75	5,990.94
Arkansas	(21,930.94)	5,218.04	(430.63)	4,389.90	21,248.15
California	572,688.35	57,749.57	185,125.65	417,479.57	(323,616.27)

¹ Numbers in thousand

The $X_{quarters}$ in equation 4.1 represents the number of quarters in this research; “1” stands for 1977 quarter 1, “2” stands for 1977 quarter 2, “3” stands for 1977 quarter 3, “4” stands for 1977 quarter 4, “5” stands for 1978 quarter 1, and “160” stands for 2016 quarter 4. Thus, the value for 2017 quarter 1 is 161. Q1, Q2, and Q3 in equation 4.1 stands for the indicator variable for quarters. Assume that forecasters wish to predict revenues in the 1st quarter, then Q1 is 1, Q2, and Q3 are equal to 0. If forecasters wish to predict values in the 2nd quarter, then Q2 is 1, Q1 and Q3 are equal to 0. Similarly, if forecasters wish to predict values in the 3rd quarter, then Q3 is 1, Q1 and Q2 are equal to 0. However, if forecasters wish to predict in 4th quarter, then Q1, Q2 and Q3 are equal to 0. Equation 4.2² demonstrates computing the predicted value in the 1st quarter of 2017, and then the predicted sales tax for Arizona is \$1,582,226,560.

$$\begin{aligned}\hat{Y}_{\text{Sales TaxesAZ 2017Q1}} &= 18,711 + 9,628.4 * 161 + 13,343.16 * 1 + 8,307.75 * 0 + 5990.94 * 0 \\ \hat{Y}_{\text{Sales TaxesAZ 2017Q1}} &= 18,711 + 1,550,172.4 + 13,343.16 + 0 + 0 \\ \hat{Y}_{\text{Sales TaxesAZ 2017Q1}} &= 1,582,226.56\end{aligned}\tag{4.2}$$

Given the sales tax for the 1st quarter of 2017, the predicted value in the actual result SAS Table 4.12 is \$1,584,530,000. This is different from the above calculation of \$1,582,226,560. Since the regression model is dynamic, once the new actual data like the 1st quarter of 2017 is added to the model, the parameter estimates are updated. Table 4.11 and equation 4.3 present the updated parameter estimates and calculation.

² Numbers in thousand

Table 4. 11: The Parameter Estimates for Arizona Sales Tax after Adding the New Actual Revenue of 2017 Quarter 1

State	Intercept	Quarters	Q1	Q2	Q3
Arizona	17,688.00	9,640.88	14,661.00	8,311.58	6,003.41

$$Y_{\text{Sales Taxes AZ 2017 Q1}} = 17,688 + 9,640.88 * 161 + 14,661 * 1 + 8,311.58 * 0 + 6003.41 * 0$$

$$Y_{\text{Sales Taxes AZ 2017 Q1}} = 17,688 + 1,552,181.68 + 14,661 + 0 + 0$$

$$Y_{\text{Sales Taxes AZ 2017 Q1}} = 1,584,530.68 \quad (4.3)$$

The actual Arizona sales tax of \$1,635,747,000 in the 1st quarter of 2017 is readily available in any statistical software. I chose to use SAS statistical software to analyze these data. Updating the sequence of 2017 quarter 1 as 161 and fitting the regression model, the predicted value and studentized residuals are obtained. Table 4.12 displays the results. The predicted Arizona sales tax of the 1st quarter of 2017 is \$1,584,530,000 (result is in thousands) and the studentized residual is 0.453.

Table 4. 12: The Predicted Value and Studentized Residual for Arizona States Tax in 2017 Quarter 1.

Output Statistics							
Obs	Dependent Variable	Predicted Value	Std Error Mean Predict	Residual	Std Error Residual	Student Residual	Cook's D
161	1635747	1584530	23980	51217	113076	0.453	0.002

Step 2: Compare the studentized residual with a critical value. This measure is based on the tail of t-distribution (which is approximated by the normal when n is large) with area 0.025 result in a value of 1.96. The studentized residual value for the 1st quarter of 2017 is 0.453, which is smaller than 1.96. As such, Arizona sales tax in the 1st quarter of 2017 is not a revenue punctuation.

If it is assumed there is no revenue punctuation, the regression model shown in Table 4.11 could be used to forecast the revenue for the 2nd quarter of 2017. If it is assumed to have a revenue punctuation, the answer to research question #2 could be utilized.

Research question #2 dealt with the patterns of revenue punctuations, and the relationship between the depth and length of revenue punctuations, if one exists. A summary of states for the five tax categories that have statistically significant relationships of revenue punctuations was given for positive punctuations and negative punctuations.

The relationships between positive and negative punctuations are demonstrated for the State of Arizona. Arizona's upper bound estimate of the relationship between depth and length is \$13,119,340 (Table 4.6), which means if positive revenue punctuation exists, the amount change from one revenue punctuation to another positive revenue punctuation could be as much as \$13,119,340 per quarter. If it is assumed next quarter has a negative revenue punctuation, the tax collection could be decreased by as much as \$31,934,740 per quarter.

This chapter investigated two research questions. For research question #1, the result revealed that except Motor Fuels Tax in the state of Tennessee, the five tax categories for each state have revenue punctuations. The method of detection of revenue punctuations relies on the diagnostic of studentized residuals.

The result of research question #2 is that not all the tax categories for each state have statistically significant relationships between depth and length of positive or negative revenue punctuations. For the state that has a statistically significant

relationship, the results could be utilized to estimate changes in the dollar amount from one quarter to another when revenue punctuation happens. For the state that does not have a statistically significant relationship, the pattern of revenue punctuations for such a state is still unknown.

The result is demonstrated using the 1st quarter of 2017 Arizona Sales Tax. In that case, Arizona was not a revenue punctuation as it did not exceed the studentized value, and the revenue forecasting for the 2nd quarter of 2017 could have three scenarios: no revenue punctuation, positive revenue punctuation, or negative revenue punctuation. Each scenario is associated with different forecasting amounts.

CHAPTER 5

DISCUSSION OF THE FINDINGS AND THEIR IMPLICATIONS

The exploratory research in this study focus on identifying U. S. state government revenue punctuations and their patterns, especially the relationship between their depth and length. This research offers many contributions, but it also has limitations in that its findings may be misused. This chapter discusses these issues in two sections. The first section lists the contributions this researcher has made to the existing body of research. There are three primary contributions. They are:

- 5.1 Identifying and describing the existence of exceptional periods of change in public and fiscal policies;
- 5.2 Recognizing the occurrence of statistical outliers in data sets and otherwise linear progressions of these data; and
- 5.3 Exploring the methods for government revenue forecasting.

The other section of this chapter will explain the implications of this research for revenue forecasting practices. The two implications are:

- 5.4 A way to reduce forecast errors; and
- 5.5 The approach to forecasting the depth and length of an exceptional period of growth or contraction.

In each of the five contributions, I briefly review the existing literature and work in this field and illustrate my research related to this field. Finally, I discuss the improvements or net contributions my research has made. Following the discussion of the five contributions and implications, I list the limitations and summarize the findings and implications of this study.

5.1 Identifying and Describing Exceptional Change in Public Policies

This research extends what other researchers have done to identify and describe the existence of exceptional periods of change in public and fiscal policies. Previous studies identified and described the existence of exceptional periods. Kingdon's (2003) "windows of opportunity" theory argued that once the problem is defined (problem stream), a solution to the problem has been developed (policy stream), and political supports have been gained (politics stream), the policy windows are open. In turn, this may cause dramatic changes in public policy. Kingdon's "windows of opportunity" theory illustrated that sudden dramatic changes do happen in public policy field.

Baumgartner and Jones (2009) were inspired by ideas from evolutionary biology to explore an extraordinary change in public policies. They posited that policies have and will develop over long periods of stability punctuated by bursts of dramatic changes, which they called "punctuated equilibrium." To prove that punctuated equilibrium does appear in public policy making, they studied U.S. federal spending and budget changes from 1791 to 2000. Using a leptokurtic approach to measure the incremental and sudden changes, Baumgartner and Jones found that federal expenditures and budgets have steady, incremental growth, but that dramatic adjustments are surprisingly common (2009).

Punctuations were also identified and described in research on government revenue collection. Groves and Kahn (1952) categorized taxes into various groups, based on the stability level of tax collections when income changes. They found that change in income tax collections have a strong relationship with changes in individuals' incomes.

When punctuations happened in income, such as recessions and stock market crashes, income taxes could become very volatile.

Fox and Campbell (1984) discovered that fluctuations in business cycles strongly influence sales taxes. In the short run sales tax collections are unstable when economic growth fluctuated, although in the long run sales taxes are not so sensitive to income punctuations.

White (1983) proved the existence of exceptional periods of change in fiscal policy. By studying Georgia state government taxes and using standard deviations to measure tax instability, White found that there are trade-offs between growth and stability of seven major taxes in Georgia.

Dye and McGuire (1991)'s research confirmed White's discovery of a trade-off between the growth and stability for taxes. However, Dye and McGuire argued general sales taxes could be separated into taxes on goods and taxes on services. The trade-offs between the government revenue growth and stability may not hold for taxes on services, they found.

Sobel and Holcombe (1997) also recognized the instability of tax collections. They advised that when estimating tax revenue elasticity, forecasters need to be concerned with both tax policy changes to the base as well as changes in tax rates.

All of these government revenue researchers confirmed that both incremental adjustments and sudden changes exist in public and finance policymaking, and government revenue collections have stability as well as volatility. In other words, previous researchers recognized that punctuations do exist in public and fiscal policies.

In contrast to other research, my work applies different methods in identifying and describing the existence of exceptional periods of change in fiscal policy. Research question #1 in my study is to identify whether there are some criteria to judge the occurrence of revenue punctuations. Concerning the statistical method of identifying outliers, I answered research question #1 by comparing studentized residuals with the critical value. If the studentized residuals were larger than the positive critical value, or smaller than the negative critical value, the data points were identified as revenue punctuations. Tables in the results chapter and Appendix B show that all the five tax categories in this study for each state have at least one revenue punctuation, except Motor Fuels Tax in the state of Tennessee. Regarding Sales Tax, Colorado, Minnesota, Missouri, Nebraska and Tennessee do not have negative revenue punctuations. For Motor Fuels Tax, Illinois, Massachusetts, New York, and Rhode Island do not have negative revenue punctuations, and Kansas does not have positive revenue punctuations. For Motor Vehicle Tax, Colorado and Georgia do not have negative revenue punctuations. In total there are 1,818 revenue punctuations among all the five tax categories: 342 for sales tax, 409 for corporate income tax, 364 for individual income tax, 334 for motor fuels tax, and 369 for motor vehicle tax. Thus, my research provided the method for identifying the existence of exceptional periods of change in tax and revenue collections.

Research question #2 is about describing the existence of exceptional periods of change, specifically focusing on finding whether the depth of revenue punctuations has a relationship with the length of revenue punctuations. In order to answer research question #2, all the revenue punctuations identified in research question #1 have been measured by depths and lengths. As defined in the methods chapter, depth refers to the changes in

dollar amount from one tax revenue punctuation to another punctuation, and length refers to the time period from one tax revenue punctuation to another punctuation. After collecting the depths and lengths data for all the revenue punctuations, I studied the relationship for all the five tax categories for each state between depths and lengths of positive and negative revenue punctuations separately. Thus, my research not only described the existence of exceptional periods of change but also explored the patterns of sudden changes.

Compared with previous research related to exceptional periods of change in public and fiscal policies, my research contributes several unique findings. *First*, it provides a specific method for studying punctuations. Researchers like Baumgartner and Jones (2009) used the leptokurtic distribution, which displayed the punctuations and incremental changes at the same time. However, theirs did not study punctuations along. Punctuations in their view exist by contrast, and their leptokurtic approach provides little information to describe punctuations any further. My research provided a greater understanding of punctuations, including their identification and their description.

Second, my research method offers a better one for scholars to identify revenue punctuations. White (1983), Boyd and Dadayan (2014) used the standard deviation to measure tax instability/volatility. However, their standard deviation method is a one-dimensional approach and only compares actual tax revenue with the mean. The primary disadvantage of the standard deviation method is that it does not count the incremental changes in dollar amount over time. The time-series data like tax revenues in this research always contains changes as time goes by even without the influence of other factors. However, the standard deviation method could not separate such regular changes

from the changes caused by other factors like economic crises. The new studentized residual method is a two-dimensional approach, which compares the actual revenues with the predicted revenues, and the predicted revenues are the same as the actual revenues that also reflect the changes due to time. With this new studentized residuals method, the identified revenue punctuations are the true outliers and do not include any changes that are purely caused by the time changes.

Third, this study explored the patterns of punctuations. Previous scholars focused on the applications of punctuation equilibrium in various policy areas, the reasons or “causes” of them, and the methods for reducing revenue volatility. However, no one studied the patterns of punctuations in public and fiscal policies. My research measured the depth and length of all the revenue punctuations and tried to explore the relationship between the depth and length of revenue punctuations.

Fourth, this research extends the scope of previous punctuation studies. Kingdon, Baumgartner, and Jones confirmed that punctuations do exist in public policymaking generally and government spending in particular, while my research provided evidence that punctuations also exist in tax and revenue policymaking. Although scholars in the tax and revenue field studied revenue punctuations, they either focused on one tax category like the income tax, or only one state like Georgia. My research looked at the top five tax categories regarding revenue collection amounts for all the states.

5.2 Recognizing the Occurrence of Statistical Outliers in Data Sets

Statisticians or statistical analysts in various social science disciplines have had no problem identifying outliers in their data sets. However, they generally end their investigation following the identification of those outliers. Hawkins defined an outlier as

“an observation that deviates so much from other observations as to arouse suspicion that it was generated by a different mechanism” (1980, p. 1). A different mechanism could be a new independent variable that affects the dependent variable, or a dramatic change to the existing independent variable. According to Kotze and Hawkins, the common method for identification of outliers is the search for residuals (1984).

Stevens stated, “regression analysis can be quite sensitive to outliers. It is important to be able to detect such points” (1984, p. 334). Stevens provided diagnostics for identifying outliers (1984). He concluded that outliers caused by recording errors, such as data collecting errors, could be deleted from the analysis. Additionally, outliers that “arise from a process different from that for the rest of the data” should be deleted (Stevens, 1984, p. 343). By “a process different,” Stevens meant the failure of a measuring instrument or the occurrence of an unusual event.

Osborne and Overbay (2004) argued much as Stevens did. They contended that outliers are caused by data errors, intentional or motivated misreporting, sampling error, unusual phenomena, application of incorrect distributional assumptions in analysis, and legitimate, but unusual cases sampled from the correct population.

Due to different features of outliers, statisticians treated outliers differently. When outliers are caused by errors or misreporting, they are removed from analysis in most of the cases. When outliers exist for unclear reasons or legitimate cases sampled from the correct population, they are kept in the analysis (Osborne & Overbay, 2004).

Following the previous scholars and researchers’ method of identifying the occurrence of statistical outliers in data sets, I used the studentized residuals to recognize

them. If the studentized residuals were larger than the positive critical value, or smaller than the negative critical value, I identified the data points as outliers.

Once the outliers were identified, I measured their depths and lengths. I defined depth as the change in value from one outlier to another outlier, and the length is the time between two adjacent outliers. After collecting the depths and lengths data for all the outliers, I studied the relationship between depths and lengths of positive and negative outliers separately. Thus, my research not only recognized the occurrence of statistical outliers in data sets but also explored the patterns of all the outliers.

I contend my approach is an improvement over standard statistical analysis and practice. Previous researchers and scholars offered many methods and tests for recognizing the occurrence of statistical outliers in data sets and guided me by utilizing studentized residuals to detect them.

However, previous researchers and scholars, much of the time ignored outliers. They believed outliers, most often, stemmed from data errors, intentional or motivated misreporting, sampling error, unusual phenomena, and incorrect distributional assumptions. Rather than studying outliers, previous researchers and scholars focused on the major trend. Researchers too seldom understood outliers as equally important clues about future trends or nonlinear aspects of data distribution and movements of phenomena over time.

Although scholars like Atkinson started to realize that “an outlier may be indicating an inadequate model” (1981, p. 860), they still focused on the effect of one or more independent variables on the parameter estimates, but they gave little attention to the patterns of outliers. My research focused analysis on the current outliers rather than

the linear trend, not only identified statistical outliers in data sets but also studied the patterns of those outliers.

5.3 Exploring the Methods for Government Revenue Forecasting

My research leads me to argue for different quantitative forecasting techniques for incremental revenue changes and punctuated revenue changes. The research also provided a new forecasting method for punctuated revenue changes. Douglas C. Montgomery and Lynwood A. Johnson stated that the methods for forecasting could be “broadly classified as qualitative and quantitative” (1976, p. 7). Per Montgomery and Johnson, quantitative forecast procedures contain two statistical mechanisms: time-series and causal models, and qualitative forecast procedures relied on subjective opinions of the experts (1976). Government revenue forecasting often uses a combination of quantitative and qualitative procedures as is the case in the relatively long-standing best practice of “consensus forecasting” (Miller, 1991; Montgomery & Johnson, 1976). However, time-series and causal models are “used to routinely analyze historical data and prepare a forecast” (Montgomery & Johnson, 1976, p. 8), and my review of the literature focused initially on the quantitative methods.

Consider what the literature on quantitative forecasting methods suggests. According to Grizzle and Klay (1994), the time-series approach includes seven methods, which are i) penultimate year method, ii) the moving average method, iii) average change method, iv) exponential smoothing method, v) linear exponential smoothing method, vi) linear regression method, and vii) curve fitting method. The explanations of these seven methods are in the literature review chapter of this dissertation.

Montgomery and Johnson argued that time-series models only use the time series history of the variable to predict the future values (1976). They recognized phenomena other than linear trends based on a survey of six characteristic patterns of time-series as Figure 5.1 displays. A constant process refers to the time-series data that has a zero rate of change over time despite small variations due to random causes. A linear trend refers to time-series data that contain a relatively constant rate of change over time. Montgomery and Johnson commented that “most time series models for forecasting are developed to represent these patterns” constant and trend or a combination of them (Montgomery & Johnson, 1976, p. 10).

Prior time-series forecasting methods explained by Grizzle and Klay are based on historical trends, which proved to be appropriate to forecast incremental changes. However, if the historical trend has only incremental changes but no punctuations, time-series models could not project sudden changes in the future. In addition, even though the historical trends have punctuations, time-series models focus on the average of the revenue trend, and punctuations might be either “averaged out,” or dropped from the analysis because punctuations might be considered as outliers in the statistical analysis.

The other mechanism that has been widely used to project government revenues is causal models. For this approach, revenue is not the only variable in the analysis. Other variables that have correlative or causal relationships with revenue have been included in the analysis as well. Researchers and scholars like Groves and Kahn (1952), White (1983), Fox and Campbell (1984), Bretschneider and Schroeder (1985), Dye and McGuire (1991), Sobel and Holcombe (1997), Hou and Seligman (2007), Cooke and McIntosh (2011), and the Rockefeller Institute of Government (2011), used economic

variables such as gross domestic or national product, personal income, and unemployment rate to project the revenue, while other scholars like Mikesell and Ross (2014), Boylan (2008), and Smith (2007) found that beyond economic factors, political acceptance, political distortions, rules, particular participants, and executive politics all influence revenue collections.

In the stock market, technical analysis is commonly used to forecast. Technical analysis for equity market studies the stock price movement in the charts, and use patterns and charts to project future price movement. The two main analytical tools for technical analysis are trend analysis and chart pattern analysis. According to Murphy, a trend is the direction of the market, which constitutes a series of successive waves in any direction, even with obvious peaks and troughs (1999). There are three directions of a trend: uptrend, downtrend and sideways.

Edwards, Magee, and Bassetti stated that the major method for technical analysis is charting and analysis of its patterns (2013). Generally speaking, there are two types of patterns found through charting: reversal and continuation (Edwards et al., 2013; Murphy, 1999). These patterns have predictive value. For example, if the charts fit reversal patterns, the future direction of the trend will be changed from the previous trend.

The details of these two methods, trend, and chart pattern analysis, are in the literature review chapter of this dissertation. In both methods, a technical market analyst can look at the shapes of the price movements and forecast exceptional periods within otherwise linear trends.

Montgomery and Johnson provided three additional patterns that might result from sudden changes. An impulse refers to the time-series data that varies due to a

temporary cause. The example Montgomery and Johnson used is a temporary sales increase in a product could be caused by a disruption at a competitor's factory. An example in government revenue collection is the one-time proceeds from sales of property. A step function refers to time-series data in which a linear trend changed to a new level permanently, with the level after the step becoming a linear trend. An example could be the acquisition of a new customer. In government revenue collection, a step might be a permanent revenue rate or base change. Finally, a ramp pattern refers to a time-series in which the rate of change increases or decreases continually over a period of time. In revenue collection, a revenue data ramp might appear as the economy of a state develops rapidly over a relatively short period of time.

The three Montgomery and Johnson examples I just discussed are variations on the basic linear trend. However, each is punctuated in some way, and the punctuation requires analysis to find what contributes to the linear trend and what does not. Montgomery and Johnson recommended that a forecaster "identify permanent changes and adjust the forecasting model to track the new process" (1976, p. 11). The phenomena creating the punctuation cannot be treated as statisticians often treat outliers. They must be treated as principal elements that have altered the forecasting model and outcome and must be dealt with separately from the linear trend.

Figure 5. 1: Time-Series Characteristics

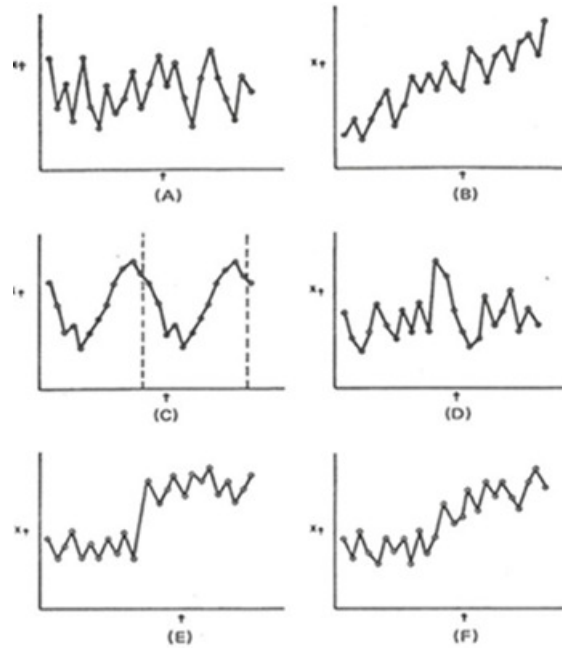


Figure 5.1 Time-series characteristics. (A) Constant process; (B) linear trend; (C) cyclic variation; (D) impulse; (E) step function; (F) ramp. Source: Montgomery and Johnson, 1976, p. 10.

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Very little discussion in the literature covers common, cyclical phenomena, which are not susceptible to linear trend analysis. Kravchuk and Stone used Indiana's fiscal crises as an example, and proposed to use a moving average as a technique to deal with cyclic variation (2010), specifically that leading into a fiscal crisis and a structural budget deficit.

Beyond cyclical trends and technical analysis and in stark contrast to the linear trend and causal model approaches to forecasting, my research proposed to use different methods when incremental and punctuated revenue changes happened. With the answers to the research question #1 in this study – how to identify punctuations - it is easy to distinguish incremental and punctuated revenue changes. If a current time-series revenue data set does not have punctuations, the conventional linear trend forecasting methods

could yield a reasonably precise revenue forecast. However, if the current time-series revenue has a punctuation and there is a likelihood of a punctuation in the next quarter, then the answers to the research question #2 –whether there is a relationship between the depth and length of revenue punctuations -- could be utilized. By knowing the relationship between depth and length of revenue punctuations, it is easy to know how much government revenue collections could change from one punctuation to another.

My research separates the punctuation from incremental changes. For punctuated changes, my research not only offers a specific way to identify punctuations, but it also describes how to explore the patterns these punctuations take. With my approach, the punctuations are neither offset by positive and negative punctuations nor dropped from the analysis.

Scholars like Montgomery and Johnson (1976), Kravchuk and Stone (2010) , Miller (1991), Edwards, Magee, and Bassetti (2013), and Murphy (1999) recognized phenomena other than linear trends and recommended to “identify permanent changes and adjust the forecasting model to track the new process” (Montgomery and Johnson, 1976, p. 11). However, except for the scholars from the various technical analysis perspectives, forecasting researchers have offered no specific methods or models to measure the depth and length of punctuations or describe the relationship between their depth and length. My research provided such methods for measuring punctuations as well as the depth and length of punctuations.

Consider one other insight gained from my research. There are a group of researchers and scholars who forecast revenues with econometrics models, all of which use other variables independent of government revenues but having correlative or causal

relationships to these revenues. However, such revenue forecast is based on the forecasted independent variables. If the independent variables, such as personal income failed to include the prediction of punctuations such as economic crises in the predicted time period, the estimated revenue could not reveal the impact of the punctuations would have either.

In addition, some of the factors that could cause or affect revenue punctuations are unknown by the forecasters, or even if they are known, the data are hard to collect. Inspired as I was by the technical analysis of equity markets, I believe all the correlative or causal relationships to revenues are reflected in the time-series revenue data itself. With my approach, there is no need to collect data on the independent variables like gross domestic or national product, personal income, or unemployment rates to project government revenues. Thus the issues related to troublesome independent variable data do not exist in my methods.

The next two contributions of this chapter discuss the implications for revenue forecasters. The first implication is for ways to reduce forecast errors. The second implication deliberates approach to forecast the depth and length of an exceptional period of growth or contraction.

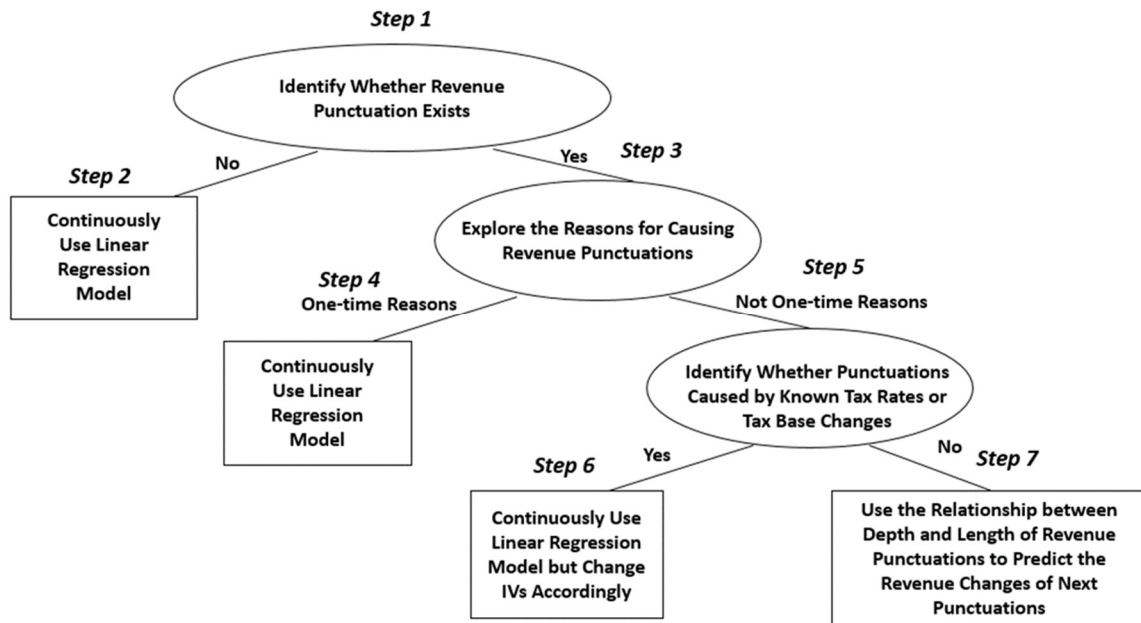
5.4 A Way to Reduce Forecast Errors

According to the research done by the social scientists at the Rockefeller Institute of Government (Boyd & Dadayan, 2014), state government revenue forecasting became far more prone to error during the last recession's turning points downward and upward due to greater volatility in revenue collections. I would argue that these errors might lie in the overreliance on linear trend forecasting rather than the careful forecast of punctuated

trends and analysis of these punctuations' depth and length. Had forecasters concentrated as much on punctuations as on linear tends, forecasters' error rates might have been smaller. In other words, one of the reasons for the high forecasting error rates is that forecasting practitioners still use the linear regression forecasting method, and pay less attention to revenue punctuations.

My research separates the punctuation forecast from the incremental forecast. Once forecasters have identified revenue punctuations, they can analyze the phenomena causing the punctuations and choose the appropriate methods to forecast the next quarter's revenue. Thus, the error rates could be reduced. Revenue forecasters could follow the seven steps diagram displayed in Figure 5.2 and steps I outline below to forecast revenues with fewer errors.

Figure 5. 2: New Practical Steps for Forecasting Revenues



Step 1: Identify whether revenue punctuation exists

Every calendar quarter, when revenue forecasters receive the actual tax and revenue collections, they could apply the methods used to answer the research question #1 of this study – how to identify punctuations - identifying whether the revenue for this quarter is a punctuation.

Step 2: Continuously use linear regression model

If the current quarter's revenue collection does not have a punctuation, they could continue with econometric linear regression models.

Step 3: Explore the reasons for causing revenue punctuations

If the revenue collection contains a punctuation, revenue forecasters need to explore the reasons for causing such punctuation.

Step 4: Continuously use linear regression model

If the revenue punctuations are triggered by a one-time issue, such as collecting or reporting errors, revenue forecasters could still use the linear revenue forecasting models to predict coming quarter's revenue.

Step 5: Identify whether punctuations are caused by known tax rates or tax base changes

If the revenue punctuations are caused by cyclical, “impulse” or “step” issues, such as economic crisis, temporary tax collection rate changes or tax rate or base changes, revenue forecasters need to apply different methods other than the typical, linear regression models. Again, revenue forecasters need to identify where the punctuation's origin lies.

Step 6: Continuously use linear regression model but change independent variables accordingly

If the sudden changes are due to tax rate or tax base changes, estimators need to update the independent variables of the linear regression models related to these two factors accordingly. Subsequently, linear regression models will be useful in forecasting revenue after the step up.

Step 7: Use the relationship between depth and length of revenue punctuations to predict the revenue changes of next punctuations

If the punctuations are due to unknown reasons or cyclical, economic crisis just as hard to predict, revenue forecasters could apply the answers to the research question #2 of this study – the relationships between depth and length of revenue punctuations - to predict how much revenue will increase or decrease between one punctuation and another punctuation.

5.5 The Approach to Forecasting the Depth and Length of an Exceptional Period of Growth or Contraction

It is hard to find any existing approach to forecast the depth and length of an exceptional period of growth or contraction, in short, a punctuation. Coming from the perspective of technical market analysis, Murphy commented that there is a relationship between height and width of stock price patterns (1999 p.102). Height in Murphy's definition is the volatility of the stock price, which is similar to the depth of revenue loss – or the height of revenue gain – in this research. Murphy's width is the amount of time for building the whole pattern, which is similar to the length of this research. Despite the ideas about stock price pattern heights and widths, Murphy did not develop an approach to forecast the depth and length of an entire punctuation.

My research tries to break new ground in forecasting the depth and length of revenue punctuations. With the correlation between depth and length of a punctuation in this research, forecasters could easily estimate how much the state's major revenues will change from one quarter to another when punctuation happens.

Several conditions or assumptions must limit the use of my approach. Otherwise, my approach can be misused. Here are the warnings for forecasters about misuse.

First, the relationship between depth and length is for an exceptional period, in other words, the relationship is only for punctuations but not for incremental changes. The adjustments other than punctuations could not apply the correlations between depth and length in this research.

Second, the relationship I discovered describes only two adjacent punctuated quarters. Before utilizing the results of correlations between depth and length, the forecasters also need to predict whether the next quarter will have a punctuation. If forecasters do not assume the next quarter will have a punctuation, my approach could not be used.

Third, I found that different relationships between depth and length exist in positive and negative punctuations. When using the results, forecasters need to assume whether the next quarter has a positive punctuation or negative one and apply the appropriate measure of depth or height.

Fourth, the data in this research are state-level quarterly tax revenues for five major tax categories. The magnitudes for depth and height are in thousands of dollars, and for length in quarters. When forecasters use my results, they need to be careful about the explanations and where they could apply the results. Forecasters could not use my

results for federal or municipal tax punctuations, although they may mimic my approach for their revenue data and develop their results to apply.

Fifth, the research question #2 is whether there is a relationship between the depth and length of revenue punctuations, and the results chapter of this dissertation shows that not all the states or all the tax categories have the relationships between depth and length of revenue punctuations. For the state or tax category that does not have a statistically significant relationship between depth and length of revenue punctuations, forecasters could not use the results.

Sixth, the relationships between depth and length of revenue punctuations in this research are explored or studied based on the patterns of historical revenue punctuations. If the patterns of future revenue punctuations are substantially different from previous patterns, then my results of forecasting the depth and length of an exceptional period of growth or contraction may not be accurate.

Seventh, the relationships I found assume length in quarters is the independent variable and depth or height is the dependent variable. When I reversed the variables in a trial run using sales tax data, to predict the length of a punctuation based on the severity of change in its depth or the magnitude of the change in its height, the results were statistically significant but the parameter estimates so small that they would seldom aid a forecaster in applying them. For example, the parameter estimate for Alabama sales tax is -0.00005947. It means on average for every \$1,000 decrease of Alabama sales tax. It could take 0.00005947 quarters when revenue punctuation happens. If I increase the magnitude of the dollar amount from \$1,000 to \$1,000,000, the interpretation will be on average for every \$1,000,000 decrease. It takes 0.05947 quarters.

Eighth, careful description by the forecaster must show the relationship that exists using my approach. For example, consider forecasters in Alabama who confirmed that the sales tax collected for the current quarter exceeds the negative critical value established for the Alabama data series. In other words, the collected revenue is too low to follow the previous trend. They then assume the next quarter will have negative revenue punctuation, since my and their statistical estimates would point to a high probability of doing so. Then he or she could state that the sales tax for next quarter could decrease by \$16,359,810, but could range with amounts not more than \$21,368,100 or not less than \$11,351,530.

In this chapter, from researchers and scholars' perspective, I discussed three contributions I have made through this research. *First*, I identified and described the existence of exceptional periods of change in public and fiscal policies. *Second*, I recognized the occurrence of statistical outliers in data sets. *Third*, I explored an alternative method for government revenue forecasting. From practitioners' perspective, I deliberated two improvements that my research has offered. *First*, my approach provided a way to reduce forecast errors. *Second*, this research proposed a new method to forecast the depth and length of an exceptional period of growth or contraction. At the end of this chapter, I also alerted the practitioners that they need to be careful about applying my research results since there were several conditions and assumptions. Otherwise, the findings could be misused.

CHAPTER 6

CONCLUSIONS AND RECOMMENDATIONS

6.1 Conclusions

Governing magazine proclaims that one of the biggest issues to watch in 2018 is state revenue projections (Farmer, 2018). It reports that in 2016, nineteen states faced mid-year budget cuts due to faulty revenue forecasts. This problem became worse. Twenty-three states faced this issue in 2017. According to *Governing* magazine, the reason more state revenue forecasters have estimate errors is that state revenue has been ominously volatile even after the Great Recession (Farmer, 2018). Unfortunately, the revenue forecasting methods that state governments applied could not successfully capture these revenue volatilities or revenue punctuations. More states experienced large revenue forecasting errors and provided the evidence that current methods for state government revenue forecasting failed.

In order to reduce the state government revenue forecasting errors caused by revenue punctuations, my research specifically focuses on studying state government revenue punctuations.

First and foremost, it extends the research scope of punctuations in public and fiscal policies to state government quarterly tax collections. My research studies the quarterly state government revenues for five major tax categories including Sales Tax, Net Corporate Income Tax, Individual Income Tax, Motor Fuels Tax and Motor Vehicle Tax for each U.S state from 1977 to 2016. The results of my research not only echo and confirm previous scholars' work that punctuations exist in public and fiscal policies, but also offers a new perspective of punctuations by revealing that tax revenue punctuations

exist in all the five tax categories across all the states, except for Motor Fuels Tax in the State of Tennessee.

Second, my research also provides a method or criterion for judging the appearance of state government revenue punctuations. Inspired by the statistical method of identifying outliers, the key for diagnosing revenue punctuations is to compute studentized residuals following models that regress taxes on quarters for each set of data points. If the studentized residual exceeds two standard errors, I declare the actual collections as punctuated revenues. With the method or criterion created in this research, scholars or revenue forecasters can identify whether or not any data point of the five major tax categories is a revenue punctuation.

Third, because of the omnipresence of state revenue punctuations, and current revenue forecasting methods only suitable for incremental changes, my research recommends the application of different quantitative forecasting techniques for incremental revenue changes and punctuated revenue changes. To reduce forecasting errors, I propose a new seven-step practical method for revenue forecasting. I have summarized this approach below.

Step 1: Identify whether revenue punctuation exists

Step 2: Continue to use the linear regression model if revenue punctuation does not exist

Step 3: Explore the reasons for causing revenue punctuations if revenue punctuation exists

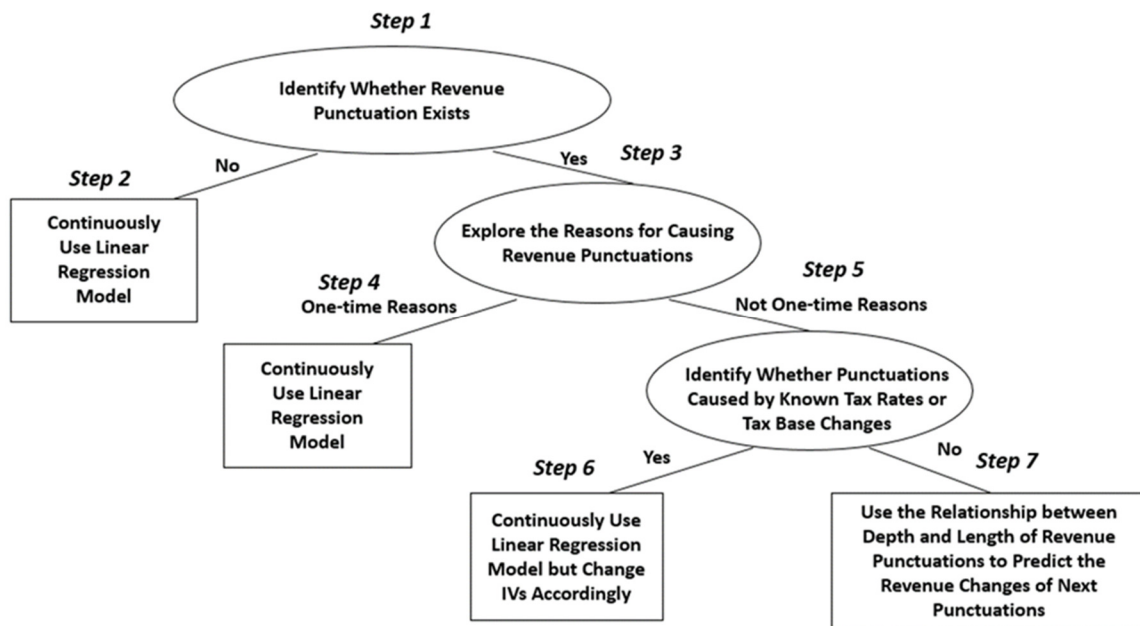
Step 4: Continue to use the linear regression model if it is a one-time revenue punctuation

Step 5: Identify whether punctuations are caused by known tax rates or tax base changes

Step 6: Continue to use the linear regression model but change independent variables accordingly if known factors cause revenue punctuations

Step 7: Use the relationship between depth and length of revenue punctuations to predict the next revenue punctuation that is not one-time and caused by unknown factors

The diagram below also illustrates the new seven-step method for revenue forecasting.



Last but not least, my research shows the patterns of state revenue punctuations, which could be utilized for punctuated revenue forecasting. Coming from the perspective of technical market analysis, which claims there is a relationship between height and width of stock price patterns, this research studies the relationships between depth and length of state revenue punctuations. Depth represents the severity of state tax revenue punctuations and is defined as changes in dollar amount from one tax revenue punctuation to another punctuation. Length represents the duration of state tax revenue

punctuations and is defined as the time period from one tax revenue punctuation to another. This research explores whether depth and length are associated with each other. The results indicate that not all of the states have statistically significant relationships between depth and length of state tax revenue punctuations. However, for the state that does, this study is able to forecast the depth and length of an exceptional period of growth or contraction if either length or depth is known.

6.2 Recommendations for Practice

At the state government level, tax revenue forecasters usually apply two techniques when forecasting revenues: economic forecast and trend (time-series) analysis. The economic forecasts are more widely applied. Some states may have a combined method of these two to estimate tax revenues. However, given that more states have larger forecasting errors, current forecasting methods have failed. According to previous studies, the faulty forecasts are primarily caused by revenue punctuations. Although revenue forecasters start to realize revenue punctuations generate the errors, it is commonly assumed that revenue punctuations are random and hard to predict, so no actions have been taken toward revenue punctuations when revenue forecasters project state tax revenues.

The findings of this research suggest that there are patterns of revenue punctuations for some states of all the five major tax categories. Thus, I recommend several improvements for revenue forecasters when they predict tax revenues:

1. **Separate punctuated revenue changes from incremental revenue changes, and apply different forecasting techniques for incremental and punctuated revenue changes.** In order to do so, I propose a new seven-step practical

forecasting method for state revenue forecasters. Following these seven steps listed in section 6.1, revenue forecasters are able to study incremental and punctuated revenue punctuations separately.

2. **Always identify whether revenue punctuation exists before forecasting.** The method or criterion of judging the appearance of revenue punctuations is provided in this research. Revenue forecasters could use the same methodology to identify the tax categories other than the five tax categories covered in this research. They could also use the same methodology to identify whether federal and municipalities' tax revenues have punctuations.
3. **Study the patterns of revenue punctuations.** If there are patterns of revenue punctuations, revenue forecasters can use the findings to forecast revenue punctuations in the future. For instance, the relationship between depth and length of revenue punctuations. Once length is known, depth can be estimated, vice versa. This research mainly explores the punctuation patterns for five major state tax categories. Revenue forecasters at federal, counties, and municipalities could also study the patterns of federal, counties and cities' tax revenue punctuations.

6.3 Recommendations for Research

Regarding improving the accuracy of state revenue forecasting, researchers and scholars nowadays focus on involving more parties including the Governor, Legislature, outside experts from academia or business and the public in the revenue forecasting process, and have consensus revenue estimation. However, less attention has been paid to revenue forecasting technique itself.

Because of the severe state revenue forecasting issues, researchers at Rockefeller Institute of Government and Pew Charitable Trusts started to pay attention to tax revenue volatility, and found that tax revenue volatility is the main reason for tax revenue forecasting errors. They even calculated a volatility score based on the standard deviation of past ten years' annual percent change for each state's overall tax revenue and major taxes. A high volatility score means revenue grew or declined more dramatically. However, these volatility scores could only indicate whether tax revenue becomes more volatile or not, but provide no information about how to improve the accuracy of revenue forecasting, so revenue punctuations are not a surprise in the future.

This research provides the evidence that revenue punctuations are not random and recommends scholars and researchers consider revenue volatility when they develop or improve the accuracy of revenue forecasting. If this is done, revenue forecasting errors caused by revenue punctuations can be reduced. The specific suggestions or future research recommendations to scholars are summarized below.

1. **Explore methods and criteria for detecting revenue punctuations.** The statistical method of identifying outliers inspired this research. Calculating the studentized residuals between actual collections and the predicted values estimated from fitted regression models, this method is able to recognize revenue punctuations if studentized residuals exceed two standard errors. Scholars and researchers may use this method to detect revenue punctuations but extend the research targets to other revenue sources like state tax revenues that are not covered in this research, or tax revenue collections at federal, county, city and town levels. Scholars and researchers could also study other

disciplines or other methods in statistics, and create their own methods for identifying revenue punctuations.

2. Study patterns of revenue punctuations to reduce revenue forecasting

errors. This research proves patterns of revenue punctuations do exist, specifically for some tax categories. It also proves that there are statistically significant relationships between depth and length of revenue punctuations. Once the length is known, depth could be calculated, and vice versa. In revenue forecasting, if it is assumed that the next quarter has revenue punctuations, the relationship between depth and length could estimate how much next quarter is changed from the current quarter. If the depth is known, with the same relationship function, it is also able to calculate how many quarters it takes from one punctuation to another. This pattern study for the relationship between depth and length of revenue punctuations came from technical analysis of stock prices. Researchers and scholars may follow this method to study the patterns of other tax revenue punctuations. However, my research also reveals that for some tax categories in some states, there are no such statistically significant relationships between depth and length of revenue punctuations. It might not be fair to conclude that for these tax revenue punctuations, there is no pattern. These punctuations may have some patterns of which I am unaware. Thus, I recommend that researchers and scholars create different methods for studying patterns of revenue punctuations. With new and creative methods, the revenue punctuations of an unknown pattern in this research may be found to have some patterns, and revenue-forecasting errors caused by these punctuations might be

reduced.

3. **Develop a new method for forecasting revenue punctuations and reduce revenue forecasting errors.** This research uses two steps to study revenue punctuations and reduce revenue-forecasting errors. The first step is identifying revenue punctuations. The second step is studying patterns of these revenue punctuations identified by step one, specifically the depth and length of revenue punctuations.

Researchers and scholars may develop a new method that only uses one step to study revenue punctuations and includes the impact of revenue punctuations in their revenue estimation model. In addition, when utilizing the relationship discovered in this research, there is always a presumption that when revenue punctuations happen, how much changes in dollar amount is associated with how many quarters it takes. In other words, this study does not predict when revenue punctuations will happen. Future research may develop a new method and focus on predicting when revenue punctuations will happen.

6.4 Personal Reflections

As a revenue forecaster for the City of Phoenix, I closely monitor the city's monthly revenue collections. I found revenue collections became more volatile and could throw off the overall accuracy of revenue forecasting. There is a faulty notion for both researchers and practitioners in the public finance field that revenue punctuations are random and cannot be predicted. Due to this misconception, no one has studied the patterns of tax revenue punctuations. Inspired by the technical analysis of equity market, I thought there might be some patterns of revenue punctuations. If patterns of revenue

punctuations are known, I am able to use these patterns to forecast revenue punctuations, and revenue-forecasting errors could be reduced. With this in mind, I started my research.

There are several challenges and difficulties when I conducted this research. *First*, I found there was no way to tell how much revenue increases or decreases could be considered as revenue punctuations, neither in theory nor in practice. As a revenue forecaster, I knew a significant percentage change or a significant amount change may indicate revenue punctuations. However, there was no universal method or criterion for identifying revenue punctuations. Although my ultimate goal was to study the patterns of revenue punctuations, without a series data of revenue punctuations, I could not study the patterns. Thus, my first research question became whether there is a criterion for judging the appearance of revenue punctuations.

Second, it is hard to decide which magnitude is used to measure changes when identifying revenue punctuations. The quarter-to-quarter changes could be measured by percentage, which is commonly used in practice. The quarterly change could also be measured by dollar amount. The measurement of percentage is highly impacted by tax collections of the previous quarter. For instance, in the change from 40 to 50 and the change from 10 to 20, the dollar amount change for both cases is 10, but the percentage changes are shown as 25% and 100%, respectively. Since the main goal is to study the relationships between changes in dollar amount and quarters it takes, using the percentage measurement for identifying punctuations may hamper the results. For this study, I used changes in dollar amount for detecting revenue punctuations.

Third, it is difficult to decide which statistical method is applied in this research when identifying revenue punctuations. I originally used the Z-score method to identify

revenue punctuations. However, the Z-score method does not reflect the incremental changes as time goes by and exaggerates the impact of revenue punctuations. After struggling for several days and testing other statistical measurements like Cook's D and Difference in Fits, I switched to studentized residual method to detect revenue punctuations.

Fourth, my original intention was to display length as the dependent variable and depth as the independent variable when studying the relationship between depth and length of revenue punctuations. The results could directly determine how many quarters it would take for one unit change in dollar amount. Unfortunately, because of the magnitude of revenue, the parameter estimate for length as a dependent variable is very small. For example, the parameter estimate for Alabama sales tax is -0.00005947. This means on average for every \$1,000 decrease of Alabama sales tax, it could take 0.00005947 quarters for revenue punctuation to occur. I increased the magnitude of the dollar amount from \$1,000 to \$1,000,000. The interpretation was that, on average, it took 0.05947 quarters for every \$1,000,000 decrease. Because it does not matter if length was the dependent variable or if depth was the dependent variable due to the relationship between depth and length being the same, I used the depth as the dependent variable instead.

Fifth, I also did several experiments to find the best fitting model for relationships between depth and length of revenue punctuations. I tested this by adding lag effect, and "sign" factors in the relationship model to capture the positive and negative revenue punctuations. It was found that separating the positive revenue punctuation analysis from

negative revenue punctuation analysis could generate the best-fitted model and I applied this method to all the five tax categories.

The above challenges are the major issues that I have experienced through this study. There are also some small difficulties including data collection, data clean up, SAS results summary, and time-management that I have encountered. It is my hope that my findings provide substantive guidance for other researchers and scholars who seek to build on this rich area of research.

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APPENDIX A

REGRESSION MODELS FOR PREDICTED TAX REVENUES

Table A.1: Fitted Models for Sales Tax

State	Intercept	Quarters	Q1	Q2	Q3
Alabama	88,190.63	3,511.02	(10,551.58)	3,711.84	(3,135.41)
Arizona	18,711.00	9,628.40	13,343.16	8,307.75	5,990.94
Arkansas	(21,930.94)	5,218.04	(430.63)	4,389.90	21,248.15
California	572,688.35	57,749.57	185,125.65	417,479.57	(323,616.27)
Colorado	40,353.16	3,970.54	5,947.30	704.17	23,678.59
Connecticut	260,649.61	5,084.54	(42,537.57)	115,209.30	(167,066.30)
Florida	(25,729.97)	36,608.35	237,557.17	181,044.33	(8,467.10)
Georgia	143,562.70	8,907.81	25,331.39	48,845.35	32,362.51
Hawaii	25,225.21	4,436.39	27,749.75	14,633.11	16,388.83
Idaho	(16,710.06)	2,411.29	(9,489.99)	(3,503.95)	15,492.02
Illinois	439,986.11	11,792.81	(94,137.59)	(57,320.61)	(18,257.97)
Indiana	98,499.05	10,131.29	14,049.70	80,844.89	63,106.08
Iowa	88,363.46	3,586.39	(18,559.47)	3,632.50	(67,901.21)
Kansas	7,439.64	4,629.42	(4,914.03)	(4,691.70)	10,072.48
Kentucky	76,706.15	4,983.72	(11,307.88)	5,631.68	8,045.81
Louisiana	116,017.08	4,642.52	3,192.79	9,126.92	1,128.76
Maine	44,447.85	1,785.14	(25,117.53)	18,018.53	(13,070.75)
Maryland	74,001.71	6,510.45	(16,472.90)	188,438.27	(209,475.99)
Massachusetts	60,355.97	8,443.36	(20,217.09)	12,660.28	13,361.12
Michigan	187,853.19	15,005.48	(128,700.66)	(29,740.51)	213,692.03
Minnesota	391,671.10	7,863.10	(264,265.90)	(55,410.56)	(277,414.44)
Mississippi	51,386.19	5,069.43	665.34	57,768.51	(25,749.62)
Missouri	189,421.19	4,596.21	5,048.83	15,745.19	27,146.51
Nebraska	(1,908.63)	2,783.97	10,616.79	17,107.37	14,089.20
Nevada	(7,649.02)	6,266.78	(57,425.90)	157,916.01	(218,611.81)
New Jersey	153,348.03	14,005.04	(155,522.73)	166,656.89	(118,486.74)
New Mexico	80,582.62	2,859.88	5,007.74	(2,788.58)	(27,644.34)
New York	529,996.39	18,068.44	(16,879.10)	(107,935.92)	16,516.90
North Carolina	(38,836.05)	10,670.24	(40,869.42)	3,514.56	12,335.54
North Dakota	(19,746.84)	1,673.62	(7,220.20)	(11,188.82)	(575.80)
Ohio	118,725.30	15,458.29	(52,001.48)	26,229.85	25,688.27
Oklahoma	15,436.20	3,910.60	(5,415.82)	396.72	7,262.89
Pennsylvania	325,531.73	14,378.85	(49,525.06)	38,316.33	27,218.52
Rhode Island	23,501.95	1,426.49	(6,082.61)	91.34	9,428.85
South Carolina	106,939.15	4,828.88	(27,326.72)	153,540.60	(97,263.27)
South Dakota	1,365.71	1,424.53	(7,815.44)	(12,226.10)	8,136.55
Tennessee	(915.72)	12,441.19	3,397.33	21,715.42	38,447.86
Texas	(573,392.11)	46,117.54	(56,685.92)	284,149.25	(15,409.10)
Utah	38,046.26	3,213.98	669.58	18,083.41	(1,801.30)
Vermont	5,814.93	577.29	333.12	(5,839.78)	(1,627.69)
Virginia	48,138.87	6,089.99	1,279.16	51,818.85	(31,058.94)
Washington	168,188.78	19,221.22	(79,192.87)	14,005.83	(892.59)
West Virginia	133,891.49	1,162.02	(2,955.15)	94.83	(5,318.20)
Wisconsin	161,753.84	7,126.77	(55,437.52)	136,385.21	(220,468.08)
Wyoming	(1,736.83)	1,293.42	(4,448.10)	(10,520.13)	4,213.72

Table A.2: Fitted Models for Corporate Net Income

State	Intercept	Quarters	Q1	Q2	Q3
Alabama	1,399.38	659.81	7,122.80	44,183.05	2,846.40
Alaska	67,576.90	420.47	(61,461.70)	67,795.60	8,783.56
Arizona	(9,512.75)	1,180.87	(21,089.21)	81,032.48	21,087.57
Arkansas	(15,035.16)	645.38	10,707.55	48,913.46	19,330.43
California	76,841.57	14,546.33	86,054.10	1,201,524.21	121,159.36
Colorado	(23,309.05)	942.36	(14,013.97)	69,011.36	15,022.51
Connecticut	47,673.75	502.37	43,596.64	136,288.35	(11,951.31)
Delaware	(9,825.54)	482.33	2,444.58	49,233.68	6,141.77
Florida	(12,977.85)	3,758.75	(50,920.47)	196,927.47	(65,060.79)
Georgia	16,885.47	1,166.86	29,377.44	107,994.32	18,596.57
Hawaii	(3,297.22)	122.13	7,557.18	27,956.59	13,121.90
Idaho	69.03	297.98	(7,055.29)	23,336.32	972.37
Illinois	(117,925.20)	5,977.36	106,042.58	329,830.24	(9,988.00)
Indiana	15,299.66	1,640.42	(69,359.76)	96,362.24	(25,177.49)
Iowa	11,458.86	385.69	(188.61)	56,074.28	(12,101.42)
Kansas	15,057.99	507.84	(21,162.60)	53,153.40	3,428.41
Kentucky	13,320.27	919.45	(33,325.28)	68,697.39	8,321.30
Louisiana	48,405.46	283.39	(51,434.97)	97,293.49	(12,167.80)
Maine	932.77	277.23	(1,472.88)	15,444.71	2,021.52
Maryland	(32,566.07)	1,557.37	31,069.56	75,022.83	15,258.99
Massachusetts	(29,759.86)	3,037.20	230,581.58	130,518.51	59,324.34
Michigan	365,575.93	(82.08)	(45,414.61)	71,214.17	20,334.04
Minnesota	21,779.50	1,738.94	39,926.86	16,862.91	8,287.31
Mississippi	(16,268.15)	715.84	49,018.43	17,327.26	9,191.13
Missouri	21,197.03	386.74	(29,444.02)	73,628.21	10,308.78
Montana	829.84	214.28	(6,789.41)	22,652.80	1,131.24
Nebraska	(6,874.18)	416.95	10,795.91	17,798.29	7,268.17
New Hampshire	(22,424.42)	1,099.83	6,483.28	34,213.28	34.92
New Jersey	61,340.93	3,508.24	(138,335.11)	336,011.24	(26,178.18)
New Mexico	3,576.46	350.45	8,755.63	11,106.71	(5,523.25)
New York	150,530.42	6,296.41	299,372.05	29,655.90	2,484.19
North Carolina	23,089.28	1,824.77	5,777.32	127,865.29	26,294.09
North Dakota	(5,289.59)	249.80	3,128.51	20,138.12	3,345.53
Ohio	42,679.51	(121.79)	252,553.56	221,634.76	9,289.83
Oklahoma	(20,887.81)	581.80	36,184.15	50,998.64	23,842.23
Oregon	1,176.35	701.55	(16,144.60)	64,929.19	18,241.00
Pennsylvania	91,303.82	2,596.22	(14,155.95)	321,972.75	(2,467.83)
Rhode Island	(5,702.59)	179.65	25,924.87	25,820.72	4,479.15
South Carolina	11,251.40	336.20	27,608.23	38,018.64	4,162.82
South Dakota	2,053.15	62.17	677.87	2,346.03	883.44
Tennessee	(70,237.06)	2,096.84	46,648.38	155,157.87	45,174.18
Utah	(16,268.02)	573.18	(4,791.35)	47,442.47	8,124.81
Vermont	(1,006.41)	150.06	3,373.14	5,998.34	1,622.72
Virginia	(2,113.14)	1,221.43	(36,151.16)	112,248.34	14,160.39
West Virginia	6,367.96	503.01	(3,235.68)	25,164.08	4,172.46
Wisconsin	23,128.78	1,193.59	65,161.63	39,030.96	24,955.68

Table A.3: Fitted Models for Individual Income

State	Intercept	Quarters	Q1	Q2	Q3
Alabama	(4,442.17)	5,514.21	(13,373.58)	56,261.62	12,924.51
Arizona	11,355.68	6,004.92	(174,811.35)	49,677.42	(19,046.94)
Arkansas	(40,885.61)	4,570.84	(31,103.58)	88,277.51	15,987.62
California	(2,445,207.57)	118,245.22	534,238.03	3,606,081.04	(64,591.33)
Colorado	(131,727.95)	10,302.41	(97,365.98)	201,764.20	3,368.25
Connecticut	(479,258.57)	15,189.40	92,122.30	573,763.54	(233,279.14)
Delaware	9,795.13	1,966.18	10,853.09	31,713.18	2,330.42
Georgia	(5,559.96)	16,790.66	(209,495.59)	45,729.19	(53,457.40)
Hawaii	32,041.41	2,827.29	(15,966.26)	10,245.68	2,762.75
Idaho	(10,994.15)	2,486.17	(24,992.04)	88,225.14	(21,701.93)
Illinois	(335,431.01)	23,283.92	351,525.82	592,941.38	37,222.46
Indiana	(88,655.96)	9,691.53	39,773.49	325,171.68	64,557.07
Iowa	80,030.13	4,767.11	(25,651.60)	49,796.72	(91,198.83)
Kansas	(35,585.94)	4,754.19	(8,519.20)	181,712.97	14,906.80
Kentucky	10,954.54	6,661.84	(61,890.58)	85,963.16	2,733.15
Louisiana	(71,392.88)	5,462.18	(39,694.53)	93,657.24	3,530.75
Maine	(5,247.90)	2,716.30	(44,830.93)	94,163.10	(21,541.30)
Maryland	47,405.57	13,068.75	(192,391.02)	278,855.43	(156,646.14)
Massachusetts	(50,432.28)	21,978.30	(578.66)	658,259.77	26,924.55
Michigan	434,813.30	11,215.24	(341,166.65)	(28,424.30)	249,723.74
Minnesota	(43,804.36)	15,220.44	(68,828.44)	307,127.89	21,039.52
Mississippi	(17,314.86)	2,987.25	(78,785.34)	63,043.70	(10,860.08)
Missouri	(63,713.59)	9,703.65	(63,394.95)	237,376.25	15,628.76
Montana	(28,733.08)	1,774.44	(4,404.07)	61,017.80	5,278.26
Nebraska	(55,262.86)	3,611.46	(6,910.09)	90,564.03	21,264.85
New Hampshire	(8,922.41)	168.18	5,358.34	27,513.09	4,587.74
New Jersey	(370,605.12)	22,865.22	87,906.69	709,007.75	(254,516.19)
New Mexico	22.44	2,240.54	(42,208.66)	14,524.01	(39,209.90)
New York	(585,015.02)	69,110.78	1,660,987.40	1,256,992.82	147,964.14
North Carolina	(69,363.62)	19,944.75	(181,388.69)	180,509.54	(38,334.19)
North Dakota	(22,595.68)	746.04	13,212.50	45,320.52	8,131.38
Ohio	68,733.81	16,518.89	1,740.78	432,550.97	40,362.07
Oklahoma	10,174.50	5,134.55	(63,869.93)	115,816.52	14,069.30
Oregon	(112,171.03)	11,546.93	(51,573.04)	293,044.03	48,579.63
Pennsylvania	(162,524.74)	18,614.15	163,320.91	598,841.07	56,352.31
Rhode Island	15,518.00	1,947.04	(35,209.64)	40,885.31	(5,794.42)
South Carolina	177,495.51	5,556.78	(338,490.26)	(79,999.35)	(121,565.99)
Tennessee	(28,159.30)	427.18	9,324.28	108,360.25	(2,183.01)
Utah	(44,075.07)	5,260.68	(100,411.63)	101,814.53	(63,691.82)
Vermont	(1,768.12)	1,116.10	(18,381.48)	34,836.19	1,010.76
Virginia	(98,712.16)	19,978.39	(242,847.33)	198,434.96	(79,035.04)
West Virginia	(26,195.14)	2,953.61	(973.78)	91,058.97	13,537.87
Wisconsin	201,623.82	11,107.25	(153,611.58)	196,089.95	(203,490.23)

Table A.4: Fitted Models for Motor Fuels Tax

State	Intercept	Quarters	Q1	Q2	Q3
Alabama	43,358.42	757.88	(2,685.40)	946.84	2,531.43
Alaska	7,498.60	19.20	(1,666.14)	(529.16)	2,086.11
Arizona	19,667.29	1,323.85	(849.85)	533.55	(1,335.99)
Arkansas	24,088.61	721.01	(3,515.00)	759.06	4,232.44
California	50,894.89	8,203.41	(21,820.88)	(8,994.18)	18,357.28
Colorado	22,562.61	1,058.88	(4,257.98)	(2,227.57)	10,340.55
Connecticut	47,447.95	634.43	(5,187.13)	17,375.67	(15,805.35)
Delaware	6,757.51	177.67	(824.93)	3,783.14	(2,244.56)
Florida	(70,827.73)	6,496.15	16,970.63	31,756.61	2,291.10
Georgia	28,725.13	1,752.54	(5,938.44)	(34.17)	5,713.34
Hawaii	7,367.72	119.38	9.52	566.35	571.35
Idaho	11,088.01	434.87	(7,089.48)	(6,724.02)	(72.84)
Illinois	104,508.17	1,932.29	4,178.13	1,580.07	12,019.66
Indiana	63,288.40	1,133.52	(8,579.32)	6,618.92	4,408.14
Iowa	50,069.83	536.59	(6,897.24)	(734.80)	(36,972.47)
Kansas	21,387.44	682.31	(3,309.53)	(369.65)	2,642.17
Kentucky	23,355.94	1,104.58	(5,154.31)	1,437.81	4,954.15
Louisiana	48,521.30	799.58	(297.02)	6,878.15	4,771.01
Maine	11,077.70	376.56	(3,161.42)	5,162.26	(4,193.55)
Maryland	39,587.89	1,358.34	(2,600.87)	39,873.23	(42,192.80)
Massachusetts	52,378.32	1,001.28	(5,430.32)	2,292.62	1,892.43
Michigan	86,092.97	1,102.91	4,449.09	16,203.25	103,596.31
Minnesota	48,531.11	1,197.91	(15,470.28)	(12,295.06)	6,435.05
Mississippi	27,827.13	622.69	(2,913.60)	1,418.89	15,653.58
Missouri	43,960.95	1,131.18	(9,826.45)	(7,249.88)	(254.22)
Montana	9,288.13	320.27	(3,920.28)	15,229.96	(1,821.91)
Nebraska	26,838.26	427.16	(5,611.81)	(1,665.62)	2,818.92
Nevada	9,145.88	552.53	(5,255.14)	18,418.91	(28,068.45)
New Hampshire	11,003.62	188.46	(599.81)	1,851.08	329.00
New Jersey	71,715.43	513.81	(6,380.34)	8,757.79	(5,383.07)
New Mexico	21,970.80	297.97	(2,671.47)	5,260.25	(3,819.23)
New York	45,503.96	1,667.91	(11,886.43)	(4,850.34)	7,617.77
North Carolina	24,227.97	3,009.50	(13,219.29)	672.64	12,234.24
North Dakota	3,778.14	304.10	(4,981.71)	(3,445.33)	267.55
Ohio	84,614.51	2,747.95	619.50	(2,950.85)	17,488.35
Oklahoma	35,849.43	618.79	(3,405.81)	(23.11)	3,207.81
Oregon	9,592.87	848.67	(271.08)	5,869.07	11,941.95
Pennsylvania	22,817.19	3,896.24	(21,682.27)	(14,550.48)	12,702.82
Rhode Island	11,884.84	147.85	(1,285.31)	(169.20)	561.71
South Carolina	35,051.11	715.33	(4,488.21)	2,807.30	5,300.24
South Dakota	12,983.99	200.91	(9,214.23)	(6,251.63)	(1,032.66)
Tennessee	63,490.85	1,234.46	(9,760.06)	2,567.14	7,570.55
Texas	78,852.85	5,578.75	(4,660.44)	24,300.04	22,994.53
Utah	9,216.78	668.63	(3,630.24)	1,676.87	481.16
Vermont	5,085.26	141.19	(682.54)	(434.73)	(234.33)
Virginia	69,342.61	1,209.93	(2,506.99)	43,471.63	(29,213.82)
Washington	17,875.35	2,045.94	(9,024.52)	25,438.18	12,905.69
West Virginia	15,317.93	599.85	(1,419.45)	(447.92)	4,414.79
Wisconsin	44,870.35	1,642.18	(11,708.15)	26,290.81	(39,559.74)
Wyoming	7,190.08	112.07	(1,605.77)	(3,049.87)	(1,676.82)

Table A.5: Fitted Models for Motor Vehicle License

State	Intercept	Quarters	Q1	Q2	Q3
Alabama	19,694.17	322.37	(11,058.42)	(10,614.08)	(11,506.50)
Alaska	(1,199.15)	112.09	223.66	4,164.35	962.47
Arizona	26,826.79	185.02	8,301.98	6,858.78	(2,916.01)
Arkansas	5,438.85	177.51	6,489.39	7,859.82	10,892.62
California	(17,256.01)	5,916.94	34,252.71	32,188.72	21,013.07
Colorado	(12,373.27)	723.31	5,237.71	2,420.50	3,602.99
Connecticut	14,525.98	243.81	3,204.02	19,590.34	4,145.79
Delaware	4,155.59	48.32	129.47	1,722.99	586.95
Florida	42,182.21	2,219.69	3,841.64	(11,037.25)	(34,202.27)
Georgia	(208.62)	563.40	18,386.95	13,348.78	(4,993.04)
Hawaii	(8,410.31)	310.59	2,474.27	3,541.63	79.94
Idaho	2,009.13	235.43	2,866.99	(678.34)	(1,912.38)
Illinois	(10,038.10)	2,585.30	15,666.12	102,560.98	89,030.12
Indiana	2,338.38	353.90	28,337.37	29,551.60	3,338.49
Iowa	2,912.65	777.15	49,609.70	4,758.50	8,011.40
Kansas	3,898.78	264.31	23,916.12	7,326.53	2,784.27
Kentucky	9,498.88	269.14	10,024.70	13,801.97	2,229.71
Louisiana	13,008.94	(27.79)	2,288.47	7,987.54	2,607.25
Maine	4,360.34	130.58	4,239.39	4,556.92	(227.35)
Maryland	(15,212.68)	789.76	16,841.41	35,273.32	7,718.58
Massachusetts	31,844.24	555.57	(17,320.05)	(7,066.34)	(27,056.21)
Michigan	14,300.29	1,533.20	58,775.74	32,558.74	12,283.70
Minnesota	16,162.76	973.37	35,196.33	22,318.52	6,747.41
Mississippi	10,187.14	207.75	(1,244.50)	(2,103.38)	(4,393.23)
Missouri	26,348.87	292.39	15,385.09	7,362.83	(1,438.78)
Montana	(4,883.00)	276.07	4,006.61	8,690.26	(3,202.24)
Nebraska	5,490.98	112.49	11,747.00	4,074.66	(578.98)
Nevada	2,445.00	296.79	2,520.26	6,699.72	(8,925.28)
New Hampshire	3,555.50	155.85	958.83	5,068.47	(3,369.90)
New Jersey	38,999.22	627.52	21,675.45	15,851.62	13,848.45
New Mexico	10,037.16	197.46	(157.51)	1,968.63	(3,329.68)
New York	43,727.51	1,690.03	3,049.39	(1,780.87)	635.58
North Carolina	(2,154.34)	947.01	62,048.13	22,342.78	9,612.39
North Dakota	3,929.29	150.52	493.46	(1,750.34)	(6,157.52)
Ohio	29,554.92	1,051.78	9,738.94	69,015.59	14,316.35
Oklahoma	19,859.49	1,062.59	14,515.51	11,309.51	3,818.28
Oregon	(2,400.37)	769.23	21,932.48	33,519.14	21,056.55
Pennsylvania	45,194.18	1,058.32	25,259.30	67,150.52	18,385.17
Rhode Island	2,606.92	69.63	5,324.30	6,331.15	94.94
South Carolina	1,677.18	222.43	7,155.18	20,592.54	(4,328.53)
South Dakota	2,544.85	91.51	3,879.66	3,078.34	954.99
Tennessee	10,743.32	332.11	16,355.89	30,463.70	5,683.07
Texas	7,118.74	2,982.27	(48,763.88)	77,429.75	23,380.17
Utah	(8,409.08)	386.27	4,222.62	5,416.33	1,634.96
Vermont	2,386.48	86.73	564.29	5,552.94	887.95
Virginia	19,323.24	563.32	14,621.27	14,999.78	8,293.99
Washington	14,427.43	894.21	(7,951.71)	(6,475.35)	(25,417.89)
West Virginia	14,941.78	(28.74)	158.64	9,720.15	4,431.20
Wisconsin	8,859.46	715.11	8,227.93	13,163.29	(7,624.31)
Wyoming	3,311.88	80.47	5,522.53	3,744.53	377.01

APPENDIX B

COUNTS OF REVENUE PUNCTUATIONS FOR FIVE TAX CATEGORIES

Table B.1: Total Counts of Revenue Punctuations for State Sales Tax

State	# Of Positive Punctuations	# Of Negative Punctuations	# of Total Punctuations
Alabama	7	5	12
Arizona	3	4	7
Arkansas	7	1	8
California	12	3	15
Colorado	2	0	2
Connecticut	2	1	3
Florida	6	4	10
Georgia	4	2	6
Hawaii	4	1	5
Idaho	6	1	7
Illinois	8	4	12
Indiana	7	1	8
Iowa	5	2	7
Kansas	5	3	8
Kentucky	5	2	7
Louisiana	7	5	12
Maine	4	3	7
Maryland	3	2	5
Massachusetts	6	2	8
Michigan	5	3	8
Minnesota	3	0	3
Mississippi	5	1	6
Missouri	3	0	3
Nebraska	3	0	3
Nevada	3	1	4
New Jersey	9	6	15
New Mexico	5	3	8
New York	8	1	9
North Carolina	7	1	8
North Dakota	5	5	10
Ohio	10	5	15
Oklahoma	7	2	9
Pennsylvania	7	1	8
Rhode Island	4	2	6
South Carolina	2	3	5
South Dakota	2	1	3
Tennessee	5	0	5
Texas	2	1	3
Utah	7	4	11
Vermont	8	2	10
Virginia	8	3	11
Washington	6	2	8
West Virginia	6	3	9
Wisconsin	5	1	6
Wyoming	4	3	7
Grand Total	242	100	342

Table B.2: Total Counts of Revenue Punctuations for Corporate Net Income Tax

State	# Of Positive Punctuations	# Of Negative Punctuations	# of Total Punctuations
Alabama	5	7	12
Alaska	4	5	9
Arizona	4	4	8
Arkansas	6	2	8
California	2	2	4
Colorado	4	2	6
Connecticut	6	2	8
Delaware	4	2	6
Florida	5	1	6
Georgia	3	6	9
Hawaii	6	4	10
Idaho	5	4	9
Illinois	5	5	10
Indiana	4	3	7
Iowa	5	6	11
Kansas	6	4	10
Kentucky	3	4	7
Louisiana	5	4	9
Maine	7	4	11
Maryland	6	5	11
Massachusetts	6	4	10
Michigan	2	3	5
Minnesota	6	4	10
Mississippi	7	4	11
Missouri	6	3	9
Montana	6	5	11
Nebraska	6	6	12
New Hampshire	6	2	8
New Jersey	5	2	7
New Mexico	5	4	9
New York	8	3	11
North Carolina	5	4	9
North Dakota	2	4	6
Ohio	8	6	14
Oklahoma	6	6	12
Oregon	6	3	9
Pennsylvania	6	4	10
Rhode Island	5	4	9
South Carolina	3	4	7
South Dakota	5	3	8
Tennessee	6	3	9
Utah	4	4	8
Vermont	5	3	8
Virginia	2	1	3
West Virginia	5	8	13
Wisconsin	6	4	10
Grand Total	232	177	409

Table B.3: Total Counts of Revenue Punctuations for Individual Income Tax

State	# Of Positive Punctuations	# Of Negative Punctuations	# of Total Punctuations
Alabama	7	1	8
Arizona	4	4	8
Arkansas	6	2	8
California	6	2	8
Colorado	5	2	7
Connecticut	4	3	7
Delaware	7	4	11
Georgia	6	3	9
Hawaii	5	5	10
Idaho	7	2	9
Illinois	4	2	6
Indiana	3	5	8
Iowa	4	2	6
Kansas	6	3	9
Kentucky	8	1	9
Louisiana	5	3	8
Maine	5	1	6
Maryland	9	1	10
Massachusetts	4	2	6
Michigan	5	3	8
Minnesota	5	2	7
Mississippi	8	5	13
Missouri	8	2	10
Montana	3	4	7
Nebraska	5	3	8
New Hampshire	3	3	6
New Jersey	6	3	9
New Mexico	4	6	10
New York	10	1	11
North Carolina	4	2	6
North Dakota	3	2	5
Ohio	5	3	8
Oklahoma	9	3	12
Oregon	5	2	7
Pennsylvania	6	1	7
Rhode Island	13	1	14
South Carolina	7	4	11
Tennessee	8	2	10
Utah	5	1	6
Vermont	5	3	8
Virginia	6	3	9
West Virginia	5	2	7
Wisconsin	8	4	12
Grand Total	251	113	364

Table B.4: Total Counts of Revenue Punctuations for Motor Fuels Tax

State	# Of Positive Punctuations	# Of Negative Punctuations	# of Total Punctuations
Alabama	2	1	3
Alaska	3	5	8
Arizona	12	1	13
Arkansas	2	2	4
California	10	6	16
Colorado	4	2	6
Connecticut	5	4	9
Delaware	3	3	6
Florida	3	2	5
Georgia	3	3	6
Hawaii	4	4	8
Idaho	6	4	10
Illinois	2	0	2
Indiana	4	3	7
Iowa	3	2	5
Kansas		3	3
Kentucky	5	2	7
Louisiana	3	3	6
Maine	4	2	6
Maryland	3	4	7
Massachusetts	3	0	3
Michigan	2	3	5
Minnesota	5	3	8
Mississippi	4	1	5
Missouri	1	2	3
Montana	2	2	4
Nebraska	2	2	4
Nevada	4	2	6
New Hampshire	4	3	7
New Jersey	5	4	9
New Mexico	8	6	14
New York	1	0	1
North Carolina	2	1	3
North Dakota	6	3	9
Ohio	6	4	10
Oklahoma	2	2	4
Oregon	8	5	13
Pennsylvania	3	6	9
Rhode Island	2	0	2
South Carolina	5	1	6
South Dakota	7	5	12
Tennessee	0	0	0
Texas	2	1	3
Utah	4	2	6
Vermont	7	4	11
Virginia	4	4	8
Washington	5	3	8
West Virginia	5	5	10
Wisconsin	4	4	8
Wyoming	4	2	6
Grand Total	198	136	334

Table B.5: Total Counts of Revenue Punctuations for Motor Vehicle Tax

State	# Of Positive Punctuations	# Of Negative Punctuations	# of Total Punctuations
Alabama	5	1	6
Alaska	4	2	6
Arizona	6	4	10
Arkansas	4	2	6
California	8	4	12
Colorado	3	0	3
Connecticut	2	3	5
Delaware	3	3	6
Florida	3	4	7
Georgia	1	0	1
Hawaii	6	1	7
Idaho	3	3	6
Illinois	3	2	5
Indiana	4	4	8
Iowa	10	4	14
Kansas	6	3	9
Kentucky	4	2	6
Louisiana	8	3	11
Maine	5	2	7
Maryland	8	1	9
Massachusetts	4	4	8
Michigan	4	4	8
Minnesota	3	4	7
Mississippi	3	5	8
Missouri	1	1	2
Montana	4	4	8
Nebraska	4	1	5
Nevada	3	1	4
New Hampshire	7	5	12
New Jersey	5	3	8
New Mexico	6	2	8
New York	6	5	11
North Carolina	4	4	8
North Dakota	4	2	6
Ohio	6	3	9
Oklahoma	3	4	7
Oregon	5	2	7
Pennsylvania	5	3	8
Rhode Island	1	2	3
South Carolina	5	5	10
South Dakota	3	2	5
Tennessee	11	2	13
Texas	5	2	7
Utah	7	5	12
Vermont	6	3	9
Virginia	4	4	8
Washington	1	1	2
West Virginia	4	4	8
Wisconsin	7	2	9
Wyoming	3	2	5
Grand Total	230	139	369