FORECASTING REVENUES FOR LANE TRANSIT DISTRICT: AN ECONOMETRIC ANALYSIS OF LANE COUNTY PAYROLLS

Brett M. Jossis, Zachary G. Penacho

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Under the supervision of
Professor Glen R. Waddell

and assistance of
Professor Timothy A. Duy

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Abstract

Seventy-five percent of Lane Transit District's revenues are received from a business payroll tax implemented on businesses within the boundaries of service. Forecasting these revenues in the past was obtained by implementing a simple growth model on previous revenues. This method is too inaccurate in deliverance because it does not accommodate for shocks (e.g. recessions). In order to more efficiently allocate resources, a regression analysis is desired to better forecast payroll tax revenues. In this paper, we present Lane Transit District with a short-term forecasting model that allows for the user to view their revenues based on the perceived probability of economic recession in the future.

Approved by:_____ _____ 9 June 2010__

Professor Glen R. Waddell Date

1. Overview

Lane Transit District (LTD) desires to forecast revenues received from the Oregon Department of Revenues. In particular, it seeks to forecast payroll taxes reported by eligible businesses in the district of LTD service, a part of which they are owed through the Oregon Department of Revenue under Oregon Statute 267.385. As part of this exercise, we will create a regression model to forecast payroll taxes across different time horizons for use in the LTD service package planning process.

This report is comprised of six sections. In Section 2 we provide some motivation and context for the problem and detail the project objectives. In Section 3 we discuss the empirical methodology we adopted. In Section 4, we we describe the data to be used in our analysis, followed by a presentation of our empirical results in Section 5. We draw concluding remarks in Section 6.

2. Project Description

The following section gives an overview of Lane Transit District's revenue model, this paper's objectives, and the merits of a forecast.

Lane Transit District provides service to the community within its district. In order to maintain its operations LTD receives funds from a payroll tax implemented on businesses within its district. Certain businesses and services are exempt from the tax, such as public school districts, non-profits and port authorities (for a complete list of tax exemptions reference Appendix A).

Twenty-five percent of LTD revenue is made up of ridership proceeds (e.g., group passes and individual payments) as well as fees paid from several constituents. The larger share of revenue is derived from local payroll taxes, which make up approximately seventy-five percent of LTD's revenue stream each year. The payroll tax was established from a funding ordinance in 1971 at a cap of 0.6 percent of every $1,000 worth of payrolls. In 1994, an ordinance established a similar self-employment tax. The payroll tax cap rate was raised from 0.6 percent to 0.7 percent by the Oregon State Legislature in 2003, with the increase phased in over 10 years according to LTD's need until the maximum rate is reached in 2014. The payroll tax in 2010 is 0.66 percent. In 2015, LTD can impose a new tax-rate cap of 0.8 percent, to be phased in over 10 years under Senate Bill 34 if it

can be determined that the economy of the community has recovered enough to sustain it.[1]

LTD addresses their budget annually to efficiently allocate their resources in a community-offered service package. LTD also makes long-term planning decisions, with ten-year horizons not being uncommon (e.g., the recent addition of the EmX line). During the decision process, it is vital for LTD to have an informed view of what the payroll-tax revenue is likely to be in the coming year as well as in longer horizons, such as ten years. Currently, LTD estimates payroll tax revenue by assessing the amount of last year's tax revenues and adding an amount based on a fixed growth rate. This method falls short of LTD's desires to forecast business cycles, and in particular, has hampered LTD's decision making in recessionary periods. The consequences of an unreliable forecast could be severe. Quite simply, if LTD under-predicts their revenue then public resources are being allocated inefficiently. Inefficiency also results from over-predicting tax revenue, but in such cases the costs are particularly acute as resources fall short of covering costs. The costs of over-prediction include cutting a service line, firing employees, or other unfavorable options. (LTD does maintain a "reserve" for such instances, but the goal is to keep the reserve minimal and not oversee unproductive capital.) It is our goal with this project to construct a forecasting model for LTD's use in the planning process.

3. Methodology

According to Diebold (2004), forecasting provides a characterization of what we expect in the present, conditional on the past, from which we infer what to expect in the future, conditional on the present and past, or, an extrapolation of observed historical data. Fiedler (1995) states, "forecasting, no matter by what method it is done, is an intrinsic part within every community's decision process."[2] In order to predict payrolls (a share of which LTD collects as revenue), it is important to know what helps them grow, or shrink. Economists are in agreement, the current system of forecasting economic activity, while flawed, is still the best available option.

It is clear payrolls are susceptive to business cycles over time. To accommodate for the cyclical nature and shocks in time series data, one operation to mellow these shocks is to incorporate a moving average (MA) process. The use of a moving average process is a common tool in forecasting. It's used to capture more of the long-term trend by softening or smoothing out the effects of short-term trends. Without a MA process, the dynamics of a model could be too reliant on the current trend. Continuing on the trend of the short-term path could have harsh implications for our model, because the current recession is causing all trends to decline. We know that the trend will eventually improve and thus

[1] http://www.leg.state.or.us/09reg/measures/sb0001.dir/sb0034.en.html

[2] Fiedler, Edgar, (1995) "The Future Lies Ahead"

we need to be able to forecast this improved trend. This is where the MA process is best put to use. To calculate the MA process, a function of current and lagged shocks is used to determine the current shock. Diebold (2004) states, "Think of it as a regression model with nothing but current and lagged disturbances on the right-hand side." This process can be done for a finite number of times, *n*, and is known as an *n*-lag operator. By allowing for a larger number of lags, we can capture a broader scope of the true dynamics of the pattern. There is a trade off, though, in that a larger number of lags create a more complicated model.

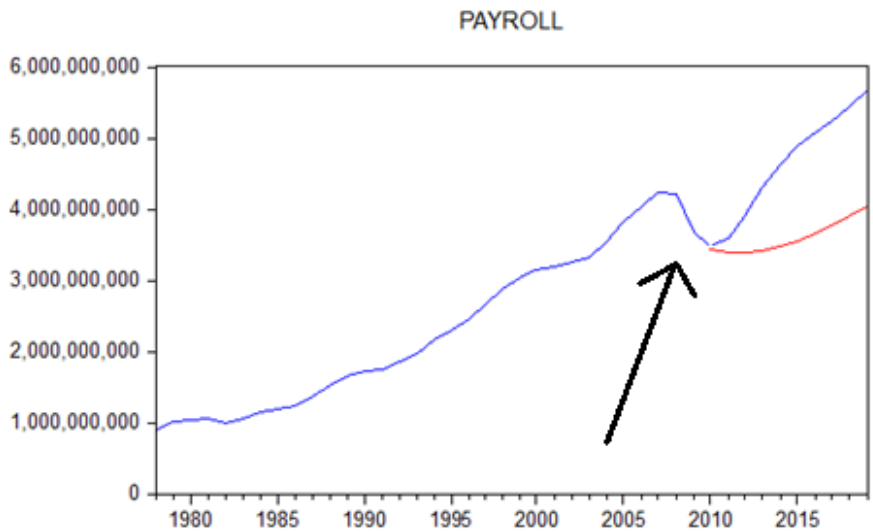
An autoregressive (AR) process is another useful tool when dealing with time-series data and is quite common in forecasting. The autoregressive process is used in stochastic models (i.e., when the current value can be explained using the past value). This process is virtually the same as the moving-average process, but instead of using current and past shocks to capture long-term dynamics, the autoregressive process uses only past values of the dependent variable to help explain current values. In a sense, it has a similar effect as the MA process of capturing the long-term pattern, but the MA is better used to smooth out recent short-term shocks to expose the model's true dynamics, whereas the AR process is best used relating current values to the long-term trends.

There are certain requirements that must be satisfied when using these forecasting tools. One important condition is covariance stationary. Covariance stationary implies that for the AR and MA models, the means (averages) and variances are constant and unconditional. An unconditional and constant mean is characterized as the expected value of the AR or MA process being constant over time. More specifically, the expected values over time average to zero. The manners in which the AR and MA processes are calculated are the reasoning behind this. The calculations, although rather simple, are unwarranted for our purposes.

The next requirement for covariance stationarity is that the variances of residuals are also constant and unconditional. Residuals are defined as the error terms. A regression model is never a true explanation of what is trying to be explained, but instead a regression is a best estimator. The error terms are the differences between the true values and the fitted (or predicted) values. One of the requirements for production of a best fit regression is that the variance of residuals equal zero. If this is not the case, then there is some explanatory power that is not being captured by the model, thus the model is not a best fit model. This fact is the same for the AR and MA processes. The unconditional aspect simply implies that the error terms do not depend on time; they are random.

The next requirement that must be satisfied when using AR and MA processes is an extremely complex and highly mathematical subject called invertibility. Without going too in depth, the MA or AR process is invertible when all the absolute values of the coefficients are less than one. If a coefficient is equal to or greater than one, the process is not applicable; this means the variable that the coefficient pertains to will have a

permanent effect on all future values. We want the effect of every variable to diminish with time. Coefficients are not always linear, and in this case, the roots of the coefficients must be less than one in order to have diminishing effects over time. The special case where a coefficient is equal to one is known as the *unit root*.



The unit root is a disturbance that permanently alters the dynamics of the data. This issue of the unit root was quite prevalent in our undertakings. The disturbance that caused the unit root is the same disturbance that caused LTD to evaluate their methods of forecasting. This disturbance is the recent recession. The graph to the left is a forecast of lane county payrolls. You can see the unit root caused by the recession. Without accommodating for the unit root, the forecast using the AR and MA processes will cause severe incline to push the data back to the original trend. This is depicted as the continuation of the blue line. We know though, that this recession will have permanent effects, and we will never reach the same trend as before the recession. But with a unit root in our data, the model assumes there will be a sharp rebound to reach the continuing trend. This is simply not the case and we must structure the model to combat this unit root so it can accommodate for it. This new forecast is depicted by the red line.

This process of detection and accommodation of a unit root is mathematically complex, but is simply achieved using statistical software. The processing of dealing with the unit root is known as taking the difference. Unit roots can vary in severity. The more severe the unit root, the more differences must be applied. Taking two differences is easily obtained using statistical software, but any unit roots requiring more than two differences can create havoc. After two differences, forecasts become complicated because what is being forecasted isn't actual values, but rather differenced values. This creates further complication and requires further dissecting to retain actual values, which allows for another margin of error. This was the case for forecasting Lane County Payrolls. Our fix for this issue is discussed in the next section.

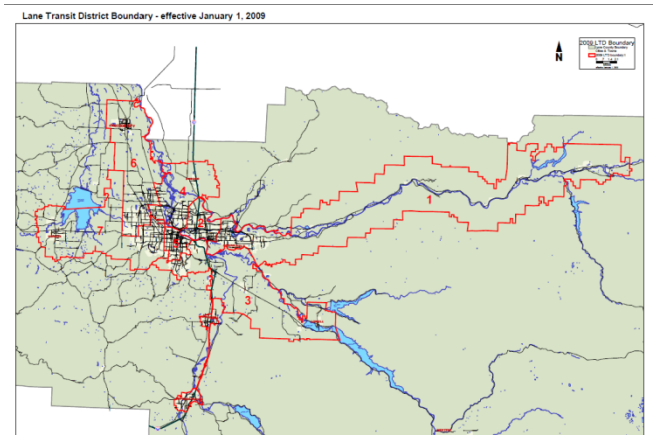
4. Data and Descriptive Analysis

This section presents our data in greater detail along with our reasoning for including certain datasets. Additional details and sources of the data are provided in the Data Appendix at the end of this paper.

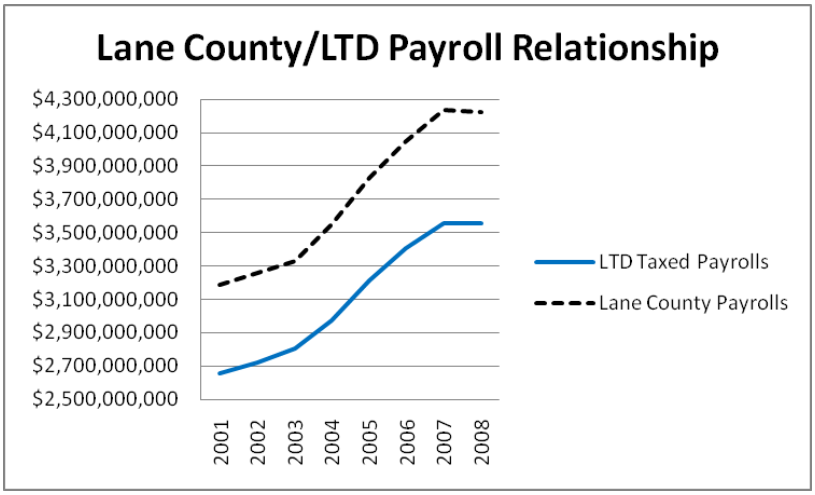
Our empirical analysis uses data of total private payrolls in Lane County, covering the period 1990 to 2009. Our data of payrolls in Lane County is broken into two parts, monthly employment numbers and average annual pay. We also examined quarterly data from LTD's Payroll Tax Database, covering the period 2001Q1 to 2009Q3.

Before moving onto the data for our empirical model, it is important to first examine the lessons learned from LTD's Payroll Tax Database. If the data was a longer time series it would have been essentially perfect for our forecasting purposes. Payrolls by nature are driven by business cycles. As an economy experiences expansion, more people are hired to support growth and payrolls tend to increase. Although not necessarily symmetric in their response, as an economy experiences recession, payrolls decrease. In order for an econometric model to forecast the cyclical nature of payrolls, the data on which the model is based must have covered previous cycles. Currently, LTD's Payroll Tax Database does not span enough recessionary periods (e.g., 1990/1). Forecasts based on existing payroll data will improve over time as periods of deep recession (e.g., 2008/9) become part of the dataset as a cycle and contribute their information to the forecasts. The LTD Payroll Tax Database does span the recession and recovery of 2001/2 and the recessionary period of 2008/9, but they don't indicate a cycle by themselves. The recessionary period of 2008/9 is such a drastic and unique shock to the data it is un-relatable to the 2001/2 recession (or almost any recession) and doesn't appear as a business cycle in a model's specification. Since this data does not yet include the rebound from the recession, a forecasting model based on this time series will tend toward zero, as if the negative growth is an entry into an apocalyptic end. Assuming that life on Earth does not end a few years from now, we deemed this data unusable to base a forecast on, but still found it useful. The data's usefulness is explained below.

Lane Transit District does not serve all of Lane County, but a subset of the community in Lane County. A representation of Lane Transit District's current boundaries is shown below in red. A select few institutions are exempt from the tax. The institutions exempt from the payroll tax are listed in Appendix A. Not knowing which part of the county's payrolls to tax and the exact companies with exemption presents a problem for using total payrolls in Lane County as a proxy for the payrolls contributing to LTD's revenue. Fortunately, with the data from LTD's Payroll Tax Database we are able to realize a relationship between contributing payrolls and total payrolls in Lane County. We first divide



annual LTD payroll tax revenue by the respective tax rate for the year, indicated in Appendix B, to derive the contributing payrolls for the year. Dividing annual contributing payrolls by the total annual payrolls in Lane County yields the percentage of contributing payrolls to total payrolls in Lane County. Under such a rule, over the 2001-to-2008 period, payrolls taxed by LTD were an average of 83.75 percent of total Lane County payrolls. The average ranged from a minimum of 83.18 percent to a maximum of 84.26 percent. The relationship is graphically depicted in the graph to the left. Assuming this relationship is recurring, forecasting total payrolls in Lane County and multiplying this output by 83.75 percent will reasonably capture total payrolls taxable by LTD.



As LTD's Payroll Tax Database grows, the data's use for forecasting will grow as well. The database's exact representation of payrolls LTD taxes will likely make it the preferred dataset once it spans the full cyclical episode (i.e., including recovery). Until then, using total private payrolls in Lane County back to 1990 and discounting those forecasted numbers to 83.75 percent of their value is the preferred method.

When statistically examining the data for total payrolls in Lane County it became clear the data had a significant unit root. Even taking the second difference of the data didn't eliminate the unit root. The significance of the unit root is due to the drivers of the data. Over time, payrolls grow as an economy grows through inflation. Inflation and a growing economy both have unit roots by themselves, and when combined, the unit root becomes more severe and thus increasingly difficult to remove. We overcame this problem by splitting total payrolls into its two inputs: number of people employed and the average annual wage. The unit root in employment is due to the shock in unemployment numbers. The recession caused unemployment numbers to have consequences that permanently altered the dynamics of payrolls. The unit root in average annual wage is also due to the recession, because as employment numbers went down, the wage growth took a severe hit. By breaking total payrolls into two components we eliminated the severe unit root, and ended up with two less severe unit roots that could be dealt with in the usual manner of taking the difference. Thus, our payroll forecast is broken up into two different models for forecasting wage and employment. The wage and employment model forecasts are then multiplied to arrive at the total payrolls forecast.

Our private employment data is monthly ranging from January 1990 to April 2010. For the employment model we are including a U.S. recession probability as one of the exogenous variables. The recession probability variable reflects the chance the economy is currently in recession. Including the recession probability variable is attractive for LTD's purposes as it allows the user to realize the level payrolls will reach given an X% of recession in the future. For instance, if LTD believes the economy has a 60% chance of entering recession in two years, they input 60% as the recession probability in the variable two years from now. The recession probabilities data is taken from University of Oregon's Professor Jeremy Piger's dynamic-factor markov-switching model, which is frequently updated on his university website[3]. For details on Piger's model refer to his paper "A Comparison of the Real-Time Performance of Business Cycle Dating Methods" (2008).

Our wage rate data is private annual average pay from 1990 to 2009. From examining the data it became clear that the wage rate in Lane County was a negative function of the county's unemployment rate. This intuitively makes sense, people are becoming unemployed because demand for workers has shrunk and as a function of the supply and demand curve, price, or wage rate, falls accordingly. Including the Lane County unemployment rate in the model required us to also come up with a forecast for the Lane County unemployment rate in order to forecast the wage rate. In regards to forecasting the unemployment rate, we deferred to the professionals. Unfortunately, a strong forecast for the Lane County, or even the Oregon, unemployment rate does not exist. The Federal Reserve Bank of Philadelphia, however, conducts a quarterly survey of professional forecasters with regards to macroeconomic quarterly and annual forecasts, such as the U.S. unemployment rate. Assuming the annual Lane County unemployment rate moves in a similar fashion to the national rate, which it generally has in the past, the model can use a forecast of the Lane County rate based off of the trend of the forecast for the national rate.

The construction of an employment and a wage model is for use when forecasting payrolls in the short-term to capture business cycles, specifically recessions. In the long-term, it is a justified assumption that the Lane County wage rate increases by about 3.23 percent each year as this is the clear average of past years. Lane County wage rates grow typically from one to five percent in a given year, but over a longer period of time, such as ten years, it is more than safe to assume the average is applicable. In regards to employment numbers, in the long-term this will also average out to typical growth as the effects of economic recessions and booms equalize each other.

5. Empirical Results

[3] http://www.uoregon.edu/~jpiger/us_recession_probs.htm

The descriptions and results of our models are discussed and presented below.

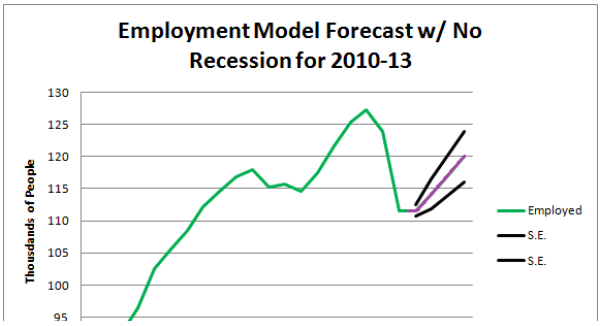
Our short-term Lane County employment model is simple. Keep in mind, when it comes to modeling, it's best to keep things as simple as possible to negate possible margins of error. It includes two AR terms, two MA terms, dummy variables for which month the data is from, and a recession probability as exogenous variables. The number of AR and MA terms was reached based on their statistical significance, relatively low AIC of this particular model and best fit. We included the monthly dummy variables in the model to account for the seasonality in employment data. The dummy variable for each month is one if the employment data is from that particular month and zero otherwise. December is used as the reference month. The endogenous variable, Lane County employment, was differenced and logged. We logged employment for two reasons, the first reason being that it provided a better fit model. The second reason is that we're not so much concerned with the numerical values, but what we're most concerned with is the change in values. By logging a variable, the endogenous variable goes from a numerical value to percent change in the numerical values. This process is completely acceptable and a common practice in forecasting models. Taking the first difference of employment eliminated the unit root that was detected in the data. Converting the differenced logged endogenous variables into numerical values is simple and costless. In mathematical form the model appears as below:

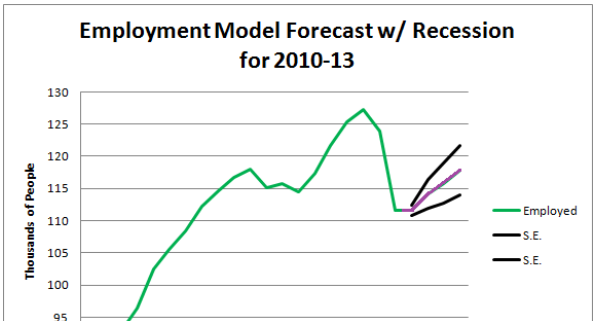
$$DLOG(Employment) = \beta_0 + \beta_1 AR1 + \beta_2 AR2 + \beta_3 MA1 + \beta_4 MA2 + \beta_5 M1 + \beta_6 M2 + \beta_7 M3 + \beta_8 M4 + \beta_9 M5 + \beta_{10} M6 + \beta_{11} M7 + \beta_{12} M8 + \beta_{13} M9 + \beta_{14} M10 + \beta_{15} M11 + \beta_{16} RECESS + \varepsilon$$

A breakdown of the model by its coefficients, error, and other details is in Appendix C.

Assuming only a one percent probability of being in a recession until 2013 (in March of 2010 there was a probability of 2.3%) the forecast (displayed to the right in purple) suggests an increase of employment in Lane County of only 46 people, or roughly flat, in 2010 compared to 2009. The forecast then displays more significant growth that predicts an increase in employment by an addition of 8,459 from 2009 to 2013, ending with roughly 120,000 people employed in 2013.

We further tested the model to see how it would perform if we imposed a quick, small recession in 2012. The model adjusts as expected and instead of reaching employment numbers of 120,000 people in 2013, employment numbers only reach 118,000.



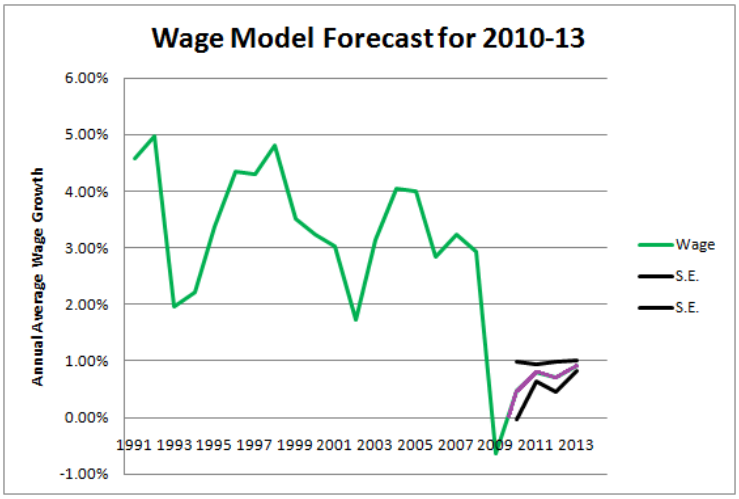


As the model is heavily reliant on the recession probability, it is important for the user to take the possibility of future recessions serious. If the economic community is discussing the possibility of a coming recession the user should impose this in the model and note what the employment number would be if the discussion were true and factor this into their planning process.

The short-term wage model is also simple. Like the employment model, it includes two AR and two MA terms, but also a variable for the Lane County unemployment rate. The same methods of choosing the number of AR and MA terms, along with the same reasoning behind taking the difference and logging the endogenous variable, were used in creating this wage model. In mathematical form the model appears as below:

$$DLOG(Wage) = \beta_0 + \beta_1 AR1 + \beta_2 AR2 + \beta_3 MA1 + \beta_4 MA2 + \beta_5 UEMP + \varepsilon$$

A breakdown of the model by its coefficients, error, and other details is in Appendix D.



Trending Lane County's unemployment rate by the trend in the forecast of the U.S. unemployment rate we forecasted average annual wage rate into the future. The model predicts wages to grow just below one percent for the next three years. This result isn't unreasonable. The economy in Lane County took a large hit, along with the rest of the country, in the last couple of years. 2009 was the first year in the data which displayed negative wage growth and it is unlikely wage growth will recover to normal growth for quite some time.

After collecting our results for the short-term employment (with 1% chance of recession) and the results from the wage rate model, we multiplied them together to realize total Lane County payrolls. We then multiplied that number by 83.75% to reach payrolls in Lane Transit District. Applying a tax rate of .66% in 2010, .67% in 2011, .68% in 2012, and .69% in 2013 we arrived at the forecast for LTD payroll tax revenues. Forecasted payroll tax revenues are given in the table on the next page.

Year	Forecasted Payroll Tax Revenues
2010	$21,159,409
2011	$22,150,689
2012	$23,212,802
2013	$24,370,217

6. Concluding Remarks

This analysis has found and created a statistical analysis tool for Lane Transit District's use when forecasting short-term payroll tax revenues. Our results and recommendations are documented below.

Lane Transit District encountered an issue when forecasting their revenues recently as a growth model was unable to account for the recession. Our model has alleviated this pain by adding a recessionary probability variable, which LTD can update based on their beliefs of the economy in the short term. LTD can also evaluate a "worst case scenario" in the short term by imposing a large recession in the next year or two and taking the model's forecast as a usable minimum for their payroll tax revenues.

From our analysis, we concluded a long-term model was unnecessary to construct in that the long run variability moves towards a mean. In the past, wage growth was around three percent per year consistently in Lane County and it is fair to assume over ten years in the future it will stay at three percent per year. Employment is effected by recessions and booms in a cyclical economy, but over time these effects average out. Recessions lower the number of people employed quickly and booms raise the number of people employed quickly. On average, these decreases and increases also average out to a growth rate. In a sense, this is how LTD was forecasting their revenues before, and in the long-term this seems appropriate. In obtaining a forecast for the long-run, we recommend using these growth rates and applying them to the short term model forecasts. Growth rates should not be calculated using values from the short term forecasts, but should be applied to the modeled forecast. Thus, the long-run forecast should begin where the short-run forecast ends. It is vital to understand that new trends are established when there are drastic shocks to the data and to start from a new trend when this occurs.

The model is best used if it is updated when actual and perceived future data is available or changes. We explored the idea of developing a "program" incorporating the model into Microsoft Excel as it would integrate easily into LTD's current operations. While the commercially available Excel software does not allow ARMA-type modeling, a third-party plug-in is available (at web-reg.de) which gives Excel the ability to perform regression analysis using an ARMA process. Unfortunately, Excel is not capable of higher mathematical functions that are often required in forecasting exercises. In particular, Excel cannot interpret the complex integers involved in the AR and MA

processes within the forecasting exercise. This shortcoming leads to inaccuracies in the estimated coefficients within the forecast, making the model valueless. We recommend LTD purchases the statistical software EViews, the same software we used to construct our model. EViews handles econometric analysis and forecasting with ease and, unlike other statistical software, has a user-friendly platform with a small learning curve. In Appendix E, we provide a tutorial to facilitate this transition, including screenshots that show how to update our model and pull forecasted data out of EViews. On the EViews website, the software sells for about $1,200.

We believe our short-term model is a strong and useful tool for LTD's purposes, but we do recognize its flaws. As our model is used for forecasting Lane County Payrolls, some of which are outside of Lane Transit District or are LTD tax exempt, its use for forecasting payrolls within Lane Transit District is only as good as the relationship between the two areas. The relationship of 83.75% seems fair as it has tightly held in the past, but as LTD expands or contracts their services, this relationship may alter, so it is recommended for future use to always reevaluate this number.

LTD's Tax Payroll database holds the exact payrolls of interest and as time goes on could turn into a very valuable dataset for forecasting (as long as the unit root is accommodated before). Another attractive quality about the data in LTD's Payroll Tax Database is its separation by industry using the North American Industry Classification System (NAICS) codes. Understanding payroll changes in specific industries is useful as it allows a forecaster to create a model based on micro-economic and macro-economic influences as opposed to only macro inputs. Creating an industry model from the exact industries, and companies within those industries, being taxed could be fruitful for an even more precise forecast in the future when the database expands.

Forecasting is as much art as it is science and it is rarely perfect. Our model gives a strong inclination of future revenues and allows for those projections to adjust based on perception. Although its results are highly unlikely to turn out perfect, they should help to illuminate the future for LTD's use in their planning process.

7. Appendices

Appendix A: LTD Payroll Tax Exempt
http://www.oregon.gov/DOR/BUS/transit-excise.shtml

LTD Payroll Tax Exempt	
Internal Revenue Code Section 501(c)(3): nonprofit and tax exempt institutions, except hospitals.	Wages paid to employees whose labor is connected solely to planting, cultivating or harvesting seasonal agricultural crops.
Foreign insurers.	Federal government units.
Domestic service in a private home.	Federal credit unions.
Casual labor.	Public education districts.
Seamen who are exempt from garnishment.	Public special service and utility districts.
Employee trusts that are exempt fror taxation.	Tips paid by the customer to the employee.
Port authorities	Fire Districts
City, county, and other local government units	Public special service and utility districts
Insurance adjusters, agents, and agencies, as well as their office support staff, are exempt from transi tax to the extent that the business income is derived from insurance-related activity. Non-insurance incor is taxable (ORS 731.840).	

Appendix B: LTD Tax Rate

LTD Payroll Tax Rate	
Year	**Amount**
1971-2006	0.60%
2007	0.62%
2008	0.64%
2009	0.65%
2010	0.66%

Appendix C: Lane County Employment Model Statistics

Dependent Variable: DLOG(EMP)
Sample: 1990M04 2010M04
MA Backcast: 1990M02 1990M03
# of Observations: 241

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.002576	0.001168	2.204837	0.0285
RECESS	-0.010758	0.001181	-9.108145	0
M1	-0.039261	0.001626	-24.15264	0
M2	0.002214	0.001659	1.334259	0.1835
M3	0.00454	0.00161	2.819749	0.0052
M4	0.008459	0.001617	5.232951	0
M5	0.008224	0.001654	4.973208	0
M6	0.008912	0.001609	5.540034	0
M7	0.000283	0.001651	0.171201	0.8642
M8	0.006699	0.001641	4.083176	0.0001
M9	-0.00055	0.001612	-0.341365	0.7331
M10	-0.003457	0.001659	-2.0837	0.0383
M11	-0.00078	0.001626	-0.479494	0.6321
AR(1)	-1.200259	0.027563	-43.54621	0
AR(2)	-0.934786	0.028868	-32.38119	0
MA(1)	1.249373	0.018662	66.94672	0
MA(2)	0.976465	0.017873	54.6322	0

R^2	0.875088	Mean DLOG(EMP)	0.000722
AIC	-7.684408	S.D. DLOG(EMP)	0.013711
Sum Residuals^2	0.005636		

Appendix D: Lane Wage Rate Model Statistics

Dependent Variable: DLOG(LWAGE)
Sample: 1993 2009
MA Backcast: 1991 1992
# of Observations: 17

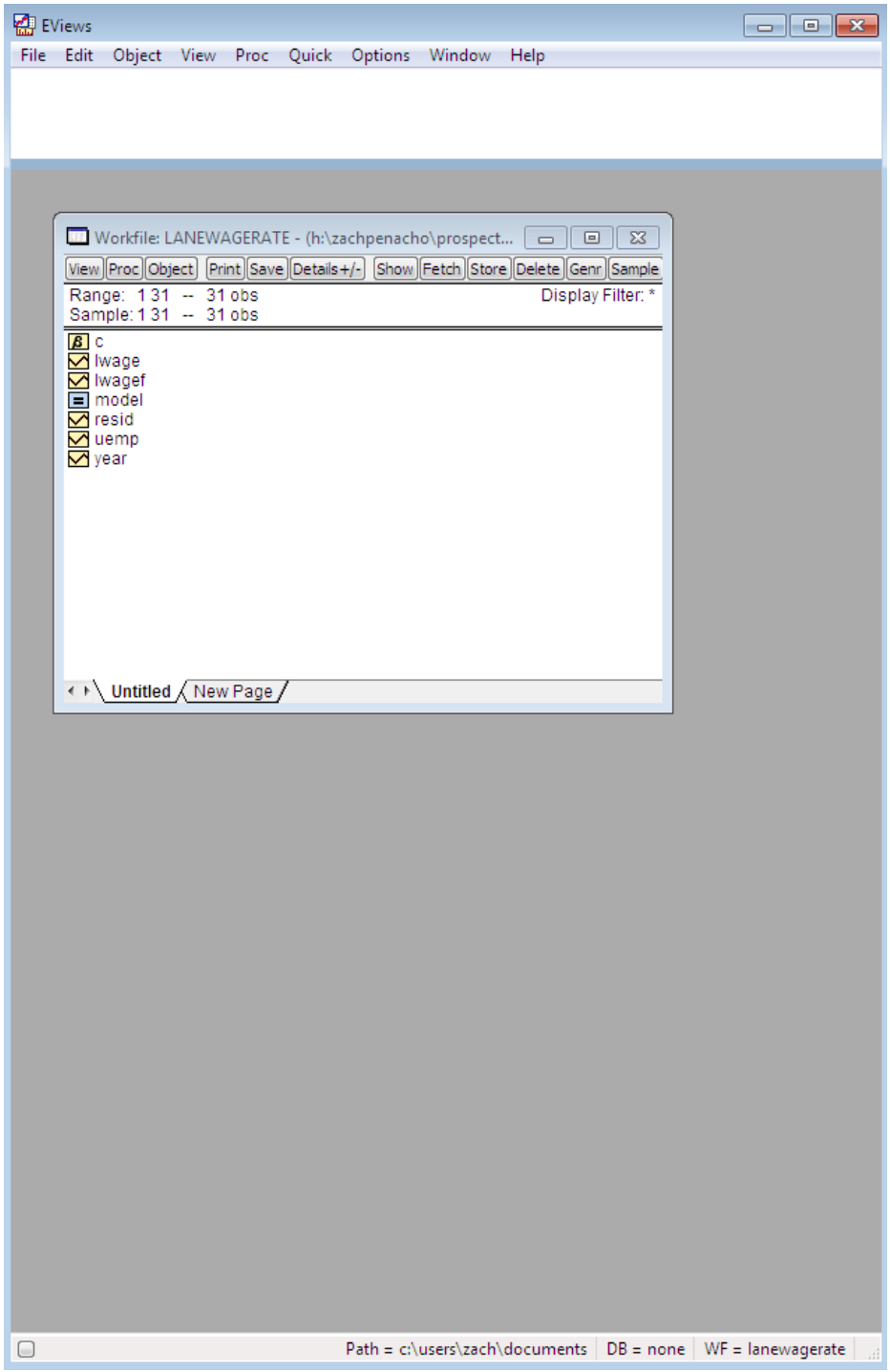
Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.072846	0.003381	21.54876	0
UEMP	-0.633325	0.053314	-11.8792	0
AR(1)	0.891551	0.151885	5.869919	0.0001
AR(2)	-0.731886	0.144676	-5.058797	0.0004
MA(1)	-1.725615	0.161565	-10.68064	0
MA(2)	0.758495	0.140054	5.415714	0.0002

R^2	0.892608	Mean DLOG(LWAGE)	0.030065
AIC	-7.523	S.D. DLOG(LWAGE)	0.012433
Sum Residuals^2	0.000266		

Appendix E: EViews Tutorial

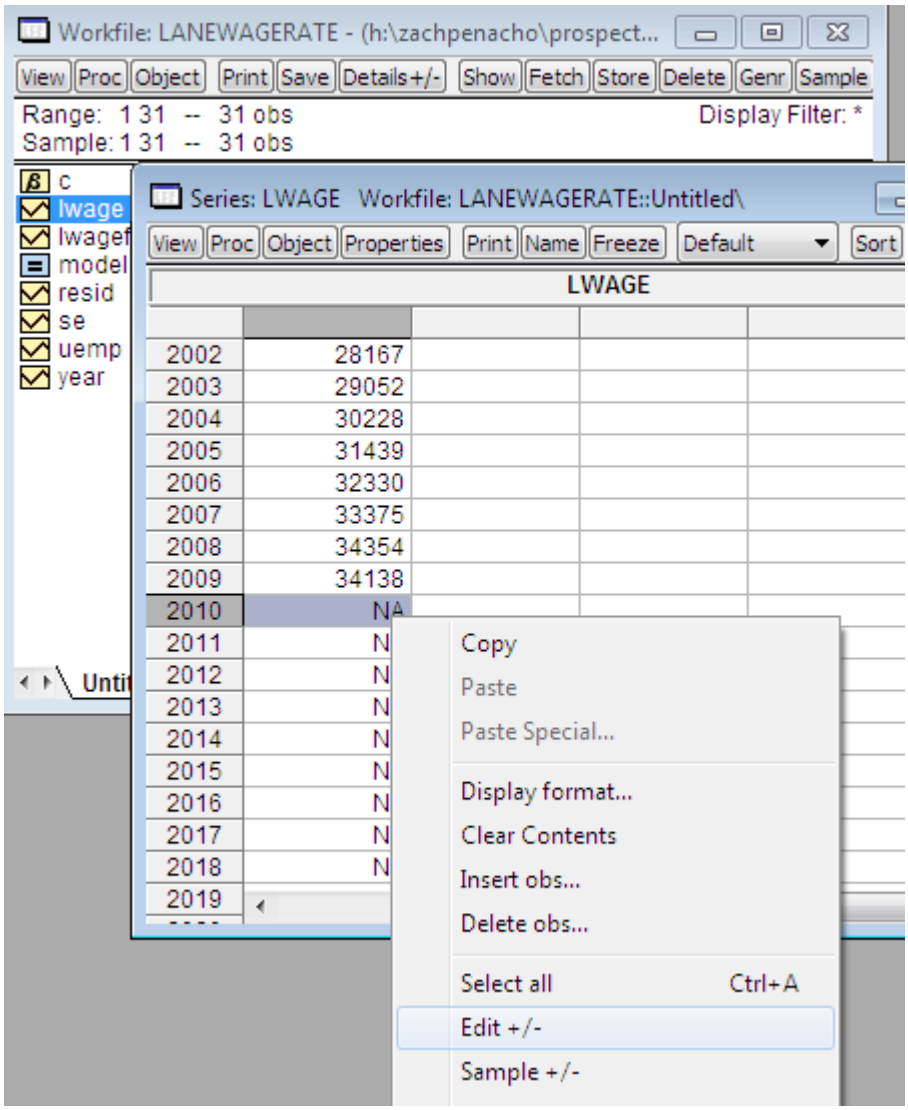
<u>Step 1 - Begin</u>

Open the EViews workfile (either lanewagerate.wf or laneemployemnt.wf). EViews will open and resemble the image below.



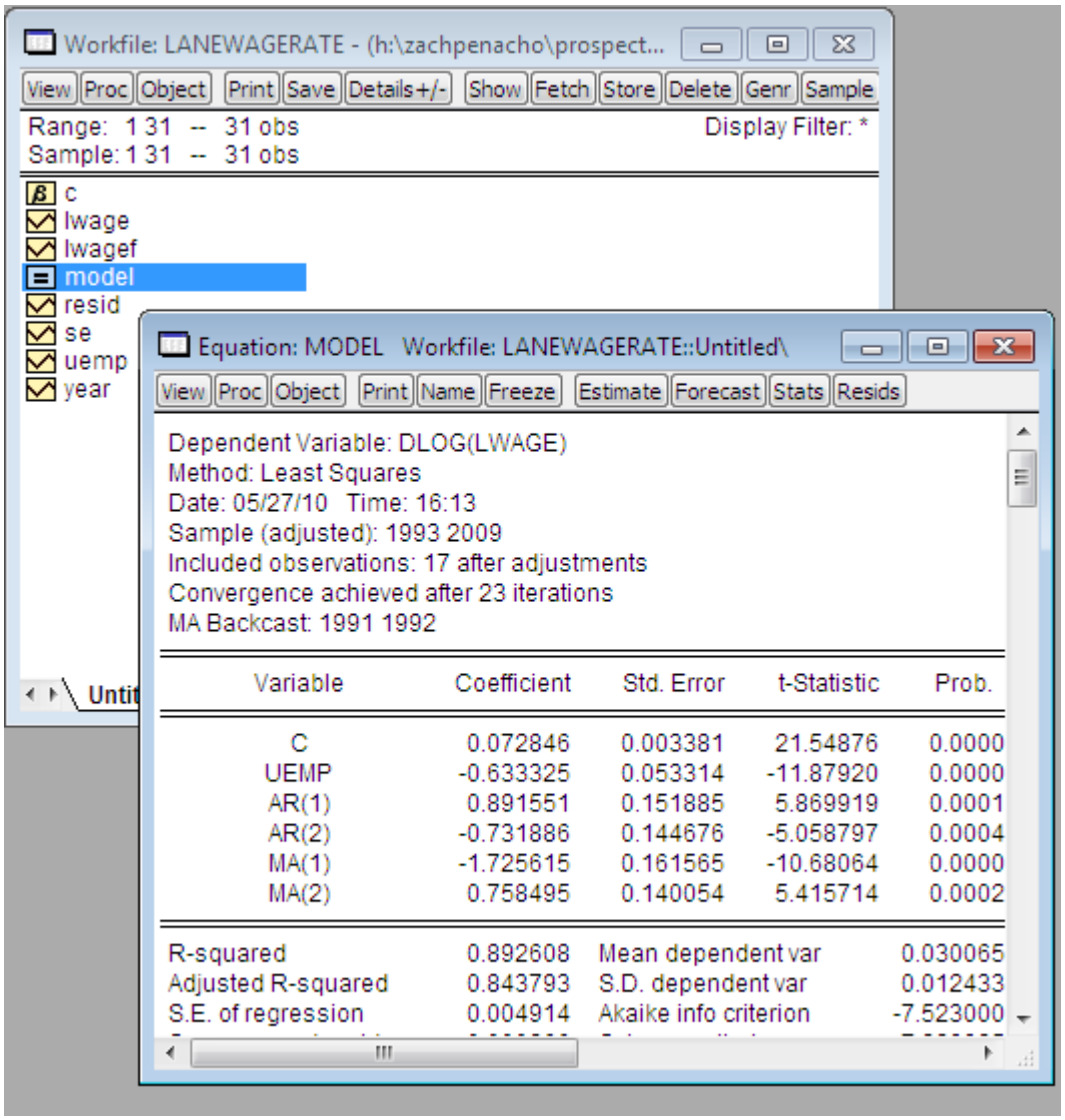
Step 2 - Add New Data

Double-click on the series you are updating. A series is represented by the yellow icon with a line going through it (resembles a graph). The series should open in a spreadsheet, if it doesn't click "View" and then click "Spreadsheet". Right-click on the cell you want to enter data into and from the menu that pops up select "Edit." You can now double-click on the cell you want to add data to and input your numbers. (For the wage model LWAGE needs updating annually based off of quality-info and UEMP needs updating quarterly based on the survey of professional forecasters. The employment model requires monthly updating as the actual employment numbers are released and the actual U.S. recession probabilities are updated.) Press enter on the keyboard and close the series.



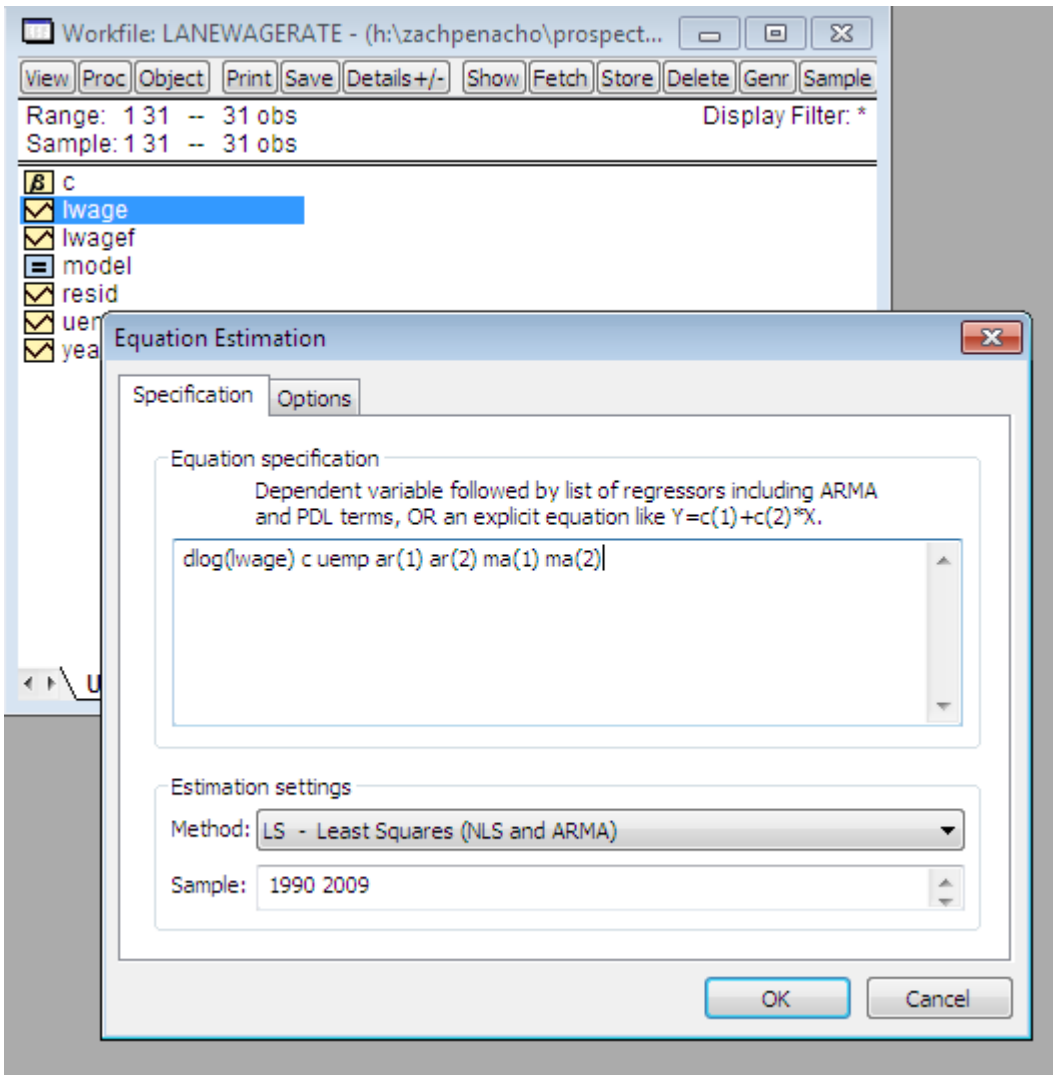
Step 3 - Open the Model (Equation)

With the new data entered it is necessary to adjust the sample size of the model to incorporate the new observations. Double-click on the model (has the picture of an = next to it) and you will see a new window like this. Click estimate.



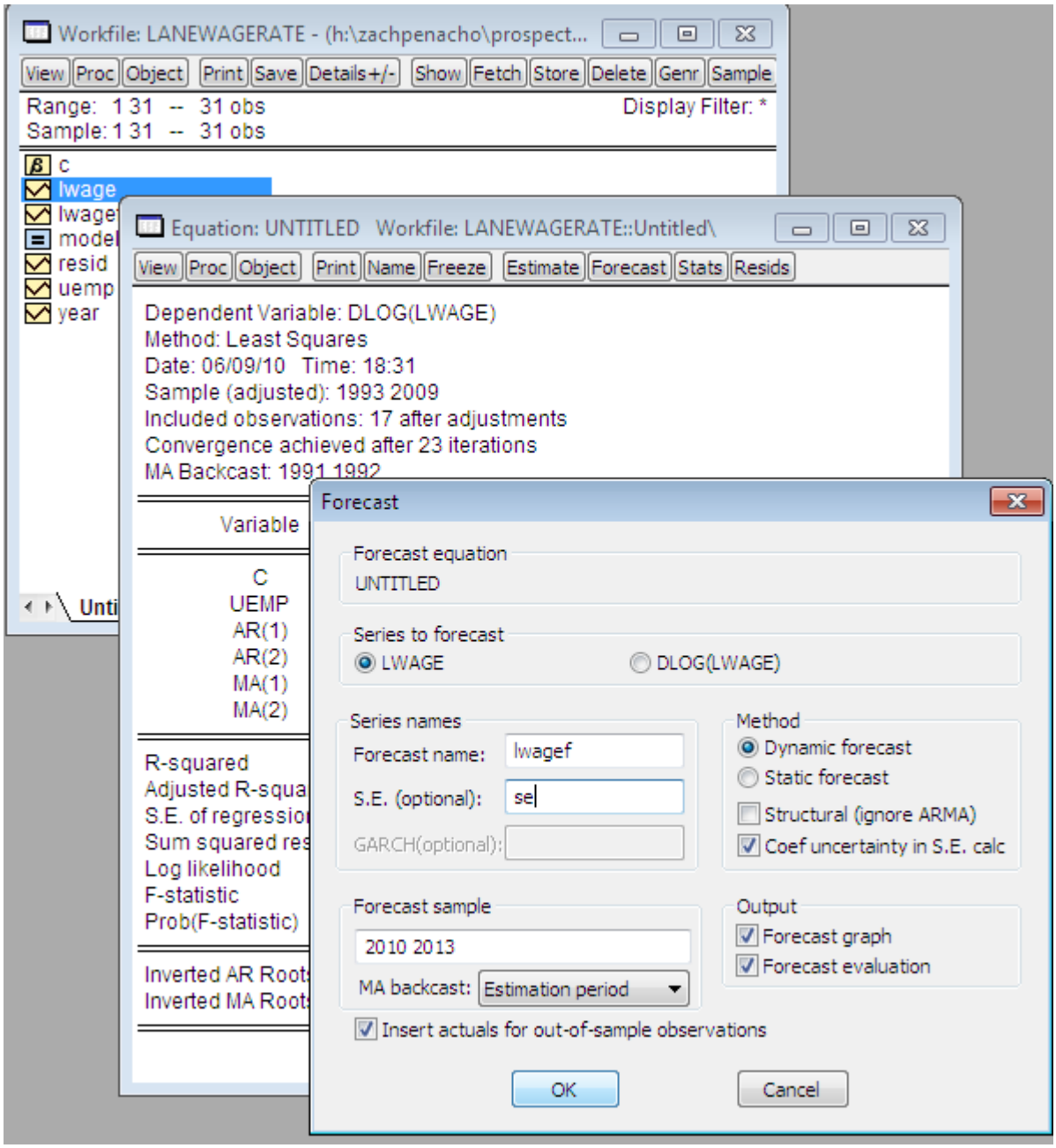
Step 4 - Adjust the Sample Size

After clicking "estimate," this window will appear. If you have added actual data you will need to change the sample. For the wage model this means changing 2009 to 2010 if you entered data for 2010. The wage model data begins in 1990 and this should be entered like below if it's not already. For the employment model you need to change the number next to month as well as the year (if you have inputted actual data for a new year). The employment model data begins in 1990m01. Press ok and you will return to the screen above.



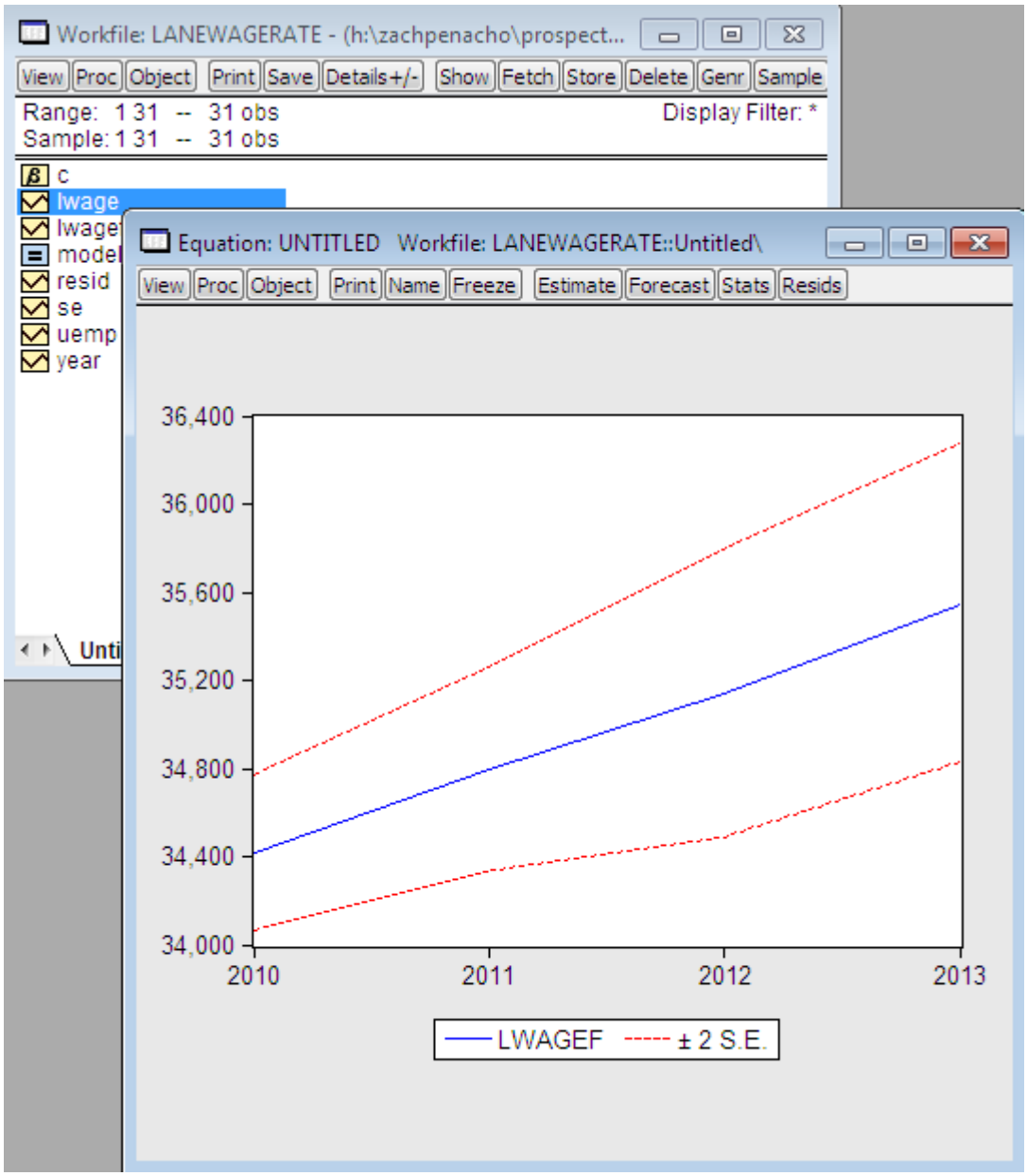
Step 5 - Forecast

Click "Forecast" on the model window and this screen will appear. All of the boxes/circles highlighted below need to be highlighted. Write in the "Forecast sample" box the time period you wish to forecast (one period ahead of the current period to the last period you are interested in) and be sure to put a space between the two periods. If you wish you can type "se" or any other name in the "S.E. (optional)" box and the forecast will return a series with the standard error of the forecast. Click ok.



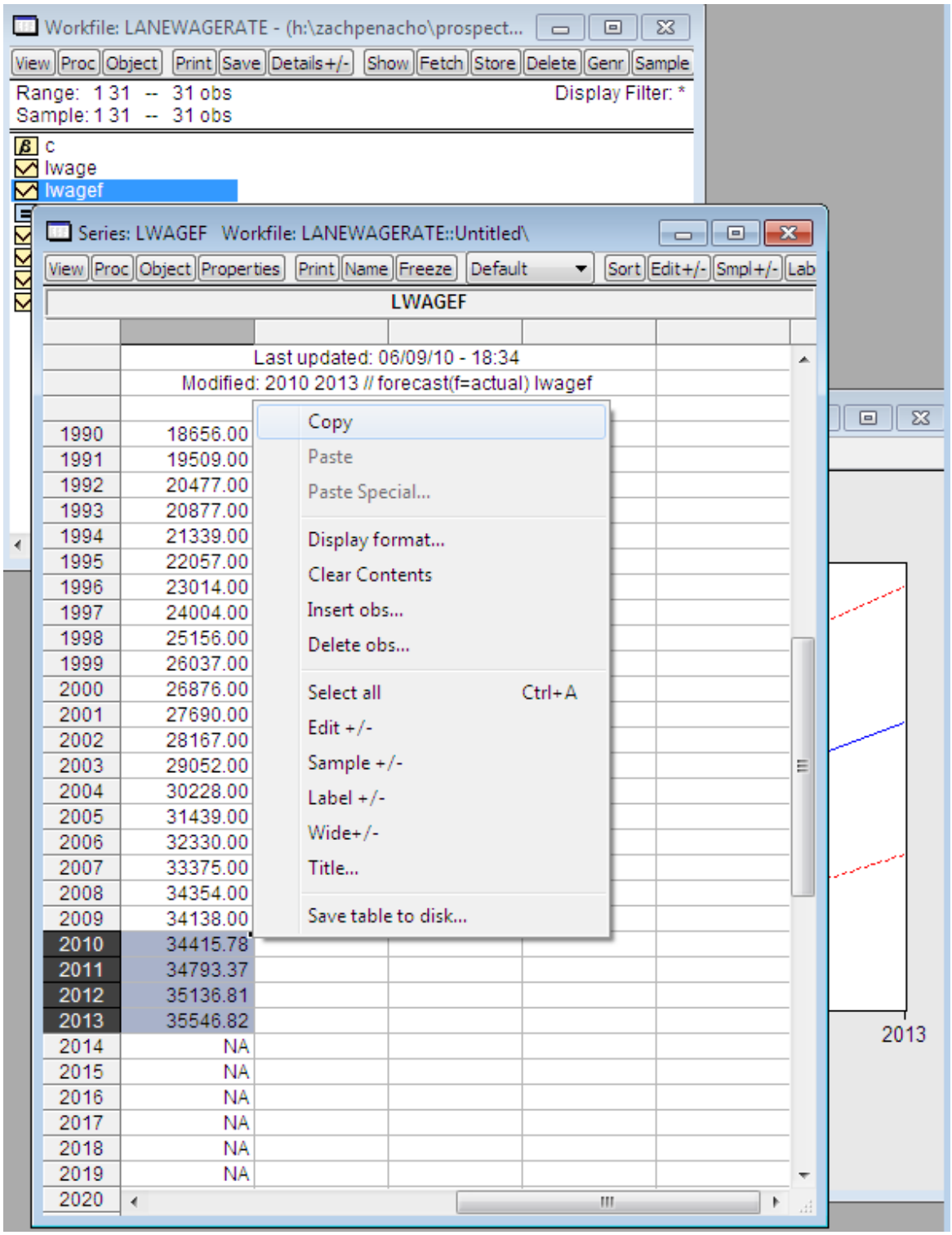
Step 6 - Forecast Result

EViews will return a graph similar to the one below. It depicts the forecast of the dependent variable as well as an error bar of two standard errors on each side.



Step 7 - Forecast Numbers

By default, EViews creates a series named the dependent variable's name with "f" on the end (e.g., lwagef). You can open the series, highlight the forecasted numbers, right-click, copy (unformatted) and then paste the numbers to another program (e.g. Excel).



Data Appendix: Data Information

Data Name	Owner	Source
Lane County Private Employment	U.S. Bureau of Labor Statistics	http://data.bls.gov:8080/PDQ/servlet/SurveyOutputServlet;jsessionid=6230364fcc9b5f81c752
Lane County Private Annual Wage Rate	Oregon Employment Department	http://www.qualityinfo.org/olmisj/CEP
Lane County Unemployment Rate	Federal Reserve Bank of St. Louis	http://research.stlouisfed.org/fred2/series/ORLANE9URN?cid=29596
Recession Probabilities	Professor Jeremy Piger	http://www.uoregon.edu/~jpiger/us_recession_probs.htm
Forecast for U.S. Unemployment Rate	Federal Reserve Bank of Philadelphia	http://www.philadelphiafed.org/research-and-data/real-time-center/survey-of-professional-forecasters/