Forecasting Unemployment with Spatial Correlation

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INTRODUCTION AND MOTIVATION

If we want to predict unemployment, one method is to build an autoregressive model that will use past values of unemployment. One drawback of this approach is the fact that unemployment data among regions is likely to be correlated in some way. If this spatial correlation is significant, it will affect the accuracy of the predictions. The main goal of this research is both to forecast the unemployment rate using a model that accounts for both spatial and temporal correlation and to compare its effectiveness to that of a univariate autoregressive model.

One may ask what is the purpose of forecasting unemployment while accounting for spatial correlation. Furthermore, it is natural to extend that question to ask why the forecast of any variable needs to account for possible spatial dependence. Giacomini and Granger (2004) show that predictions built from models that ignore such relationships are less accurate than those that ignore spatial correlations. So if we are to build forecasts that contain spatial correlations between neighboring regions, it is important to use a structure that will assess their strength and consider their presence.

More specifically, there is much gain to the accurate forecasting of unemployment. Consider a local unemployment office preparing to set up its training program and budget for the coming months. It receives forecasts of unemployment in order to make the necessary preparations for the number of people it expects will come to visit in the upcoming period. If the values have been predicted naively without considering spatial dependence and they are inaccurate, the local office will either have excess resources sitting idle for that month or have to scramble to acquire more. If the model factors the spatial dependence into its predictions and produces more accurate forecasts, the local office will benefit by spending more time concentrating on the unemployed workers coming in for help rather than making ends meet. Now imagine this scenario on a statewide or national scale. This is just one example of how better predictions for unemployment can help to serve society.

This can hold true for any variable that may contain a spatial component. Some examples of such variables are consumption, prices, or shocks to either demand or supply. If we are interested in attempting to forecast any of these variables (or others) and believe that their future values will not only depend on the history of the region but also the past values of surrounding regions, then the model we build must account for this dependence.

LITERATURE

Predicting unemployment is an active field of study. Montomery et. all (1998) attempt to compare several types of models used to forecast unemployment, including nonlinear models. They specifically look at univariate linear models, threshold autoregressive models, Markov switching autoregressive models, and disaggregation over time. They find frequency of the data determine the best model for a given situation. Threshold autoregressive and Markov switching autoregressive structures are shown to be the most accurate when using quarterly data, while the autoregressive moving average was best for monthly data. Proietti (2003) also analyzes the effectiveness of time-series forecasting models of U.S. unemployment. His work is more concerned with the temporal relationship between business cycles and unemployment, and does not discuss spatial correlation.

Before building a model for forecasting unemployment, it is necessary to identify the conditions of any spatial correlation present and determine its type and structure. Cliff and Ord (1973) describe a general structure of spatial correlation which can be applied to correlations in unemployment rates between counties. To state more formally, "If for every pair of counties i and j in the study area the drawings which yield x_i and x_j are uncorrelated, then we say that there is no spatial autocorrelation in the county system on X (p.2)." The opposite is also true; if a relationship is found between the counties, this would be identified as spatial correlation. Griffith (1987) goes further in his definition of defining positive and negative spatial correlation. To put it in the language of this research, if high (low) values in one county are accompanied by high (low) rates in those counties that share its border, we have evidence of positive spatial autocorrelation.

Conversely, if high (low) values in county i appear with low (high) values in its neighbors, this is negative spatial autocorrelation.

If spatial correlation is present and significant in the data, it is likely to take one of four distinct forms described by Haining (1990). The first is diffusion, which measures the speed of a development process. A common example is the rate at which a population adopts a new product upon introduction. The second structure is exchange and transfer. This type of dependence can be seen where income earned in one area is spent in another. Exchange and transfer can be captured using a spatial correlation model. Interaction is the process where the events of one region have an effect on its neighbors. For example, price changes in one store can have an effect on other similar stores in the area, which may result in a price pattern within the area. The final structure is called dispersion. This measures the density of the population. The spatial correlation in this process is dependent on the dispersion of the population itself rather than a common factor such as unemployment. For example, it is possible that more densely populated areas suffer from a higher unemployment rate than others that are less crowded.

The next issue to address is whether or not spatial dependence is present in unemployment. Bronars and Jansen (1987) propose modeling unemployment both spatially and temporally in the United States. They use monthly data collected from surveys on county unemployment rates, and aggregate the data to avoid the possibility of measurement error. The authors also difference out the current period's U.S. unemployment rate at that time period to avoid any possible spurious correlation. After removing seasonal trends from the data, they have a measure of the deviation of the local unemployment rate from the aggregate mean.

Bronars and Jansen (1987) initially find that distance and spatial correlation are inversely related. They also note that the relationship between the component (the piece of the aggregate, i.e. county in a state) and the unemployment rate for the neighbor last period, the first temporal lag of the first spatial lag, is negative. This implies that the reaction in a component to a labor shock is quite different from that of its surrounding areal (regional) units.

The authors also considered the importance of population density. Using two regions on either side of the Mississippi River, they find that the western region (which is the less dense of the two) has a stronger temporal relationship but a weaker spatial relationship between the components. These differences however are not found to be significant, so the authors combine the regions for this analysis. Bronars and Jansen (1987) do find through a simulation that shocks to a labor market can have effects that will span in the neighborhood of twenty-five miles, provided that it is a relatively permanent shock.

Now that we have established the possibility of spatial correlations across regions, the next step is building an appropriate model to capture their effect. The first question is the structure of the spatial autocorrelation. Cressie (1993) describes different ways the composition of the correlation could be arranged. Using lattice data, which is broadly defined as data that is ordered in spatially regular intervals linked to its neighbors by common borders, there are multiple ways of setting up the model. One way is to specify neighborhoods of the areal units by distance. The first step is specifying a certain distance from the i^{th} county. Any county within this range is classified as being in the i^{th} county's neighborhood. A second method of building a neighborhood is to classify counties sharing a border with the i^{th} county as being in the i^{th} county's neighborhood. This can be extended beyond the first border to other counties sharing a border with the initial county if desired.

In either case, we need to construct a proper weighting matrix to accurately depict the strength of the correlations between the counties. Cliff et al. (1975) describe a simple case relating to border-sharing areal units. Merely restricting the regions of interest to those touching can still leave a complicated structure. He describes three cases of bordering that can arise from a simple lattice. These are the rook's case (common edge), bishop's case (common vertex), and queen's case (common edge and vertex). Note that in these three situations each has its own matrix. The rook's case matrix would give weight to neighbors in the cardinal directions from the county, while the bishop's case matrix would only consider those in the ordinal directions. The queen's matrix is also unique; it is a combination of the previous two. It is important to note that even if the model is properly constructed in every aspect with the exception of this matrix, this incorrect specification can lead to inaccurate forecasts.

Stetzer (1982) analyzes how to properly construct this matrix in "Environment and Planning A." Using a series of Monte Carlo experiments he finds that for forecasting purposes using true weights is in general the most effective method. "True weights" refers to the accurate representation of the strengths of the respective spatial relationships. These are the correlations that accurately describe the relationship between counties. In practice the matrix that represent the true weights will be extremely difficult to precisely estimate since they will not be known at the time one constructs the forecasts. However in the absence of these true weights, “ there is usually an alternative weighting scheme which produces forecasts with accuracy within 1% of the accuracy of the true weights, as measured by average absolute error (p. 583).” Stetzer (1982) continues by showing that in general the most important goal is matching the effective area. The effective area is the size of the region that for a particular county i, the value of the weight assigned to its neighbor is nonzero, while any component which is spatially distant enough to be assumed to have no areal dependence would be given a weight of zero. Finally, if the area is large it is important to use weights that decay with distance. If the effective area is small, the most important concern is to match the effective area.

Once we have determined the structure of the spatial autocorrelation and properly defined the weights associated with their corresponding areal units we can then begin to construct the model to use to build forecasts. The important factor here to consider is which model will be most effective in predicting state’s unemployment rate based on county level data. Brown et al. (2000) considers a space-time model that is affected by dispersion of the variable under study. If the spread of the correlation is sufficient to cause distorting noise in the model, the separability of the covariance functions becomes difficult if not impossible. The authors propose that if such dispersion is present in the data, a proper blurring function can be used to smooth the noise and make inference possible.

J. Paul Elhorst (2001) considers the presence of spatial correlation in dynamic models. He compares a simple dynamic space-time model (DSTM) with other common constructions, mostly other space-time combinations. that are generally used to analyze this type of data. It specifies an equation that uses the following regressors: the first temporal lag of the dependent variable, a weighted index of the first temporal lag, a value of another similar variable that is expected to have spatial dependence (neighbor), the first temporal lag of the neighbor, and the weighted values of both the neighbor at time t and the first temporal lag of the neighbor. The weighting matrix he uses is chosen ex ante using known spatial correlations between the regions. He first compares the DSTM with a typical time-series model. This framework includes both the first temporal lag of the dependent variable and as well as the time t value of the neighbor and its first temporal lag. He also compares the DSTM to a simple cross-sectional model and a combination of the previous two models (which is similar to the DSTM absent the weighted values of the spatial and temporal lags). He finds DSTM to be the most effective predictor as it considers the strength of the spatial dependence instead of assuming a common weight across all areal units.

Elhorst (2001) proposes that using the dynamic model as the first step and narrowing down the equation to make it fit the specific data will be the most effective way in specifying an equation. In other words, when building a model to capture these spatial and temporal relationships, starting with a simple static model and correcting for either type of correlation is not the recommended course of action. Because most economic data is likely to contain some form of both types of correlation at least to some degree, it is better to start with a general model and work toward a more specific structure than to start with a narrowly defined particular model and work to make the necessary corrections. The author also brings up and dismisses the possibility of using a fixed effects or random effects model on panel data, because such a model becomes more difficult to estimate and less clear to interpret if both a spatial and temporal lag is included.

Simply identifying the presence and structure of spatial correlation is not enough to properly build the most accurate model. As the papers in this section show, there are auxiliary problems that arise when the data is subject to spatial dependence. Once these possible problems have been resolved, one can continue to build the appropriate model and use it to forecast the variable(s) of interest.

Once we have built the model to predict the individual counties' unemployment rates, the next step in the process is to use these forecasts to build an aggregate prediction for the state. At this point, it is important to focus on any implications of using these estimated county values to make predictions for the aggregate. For example, are there any complications in using county data in building forecasts for the state? Grunfeld and Griliches (1960) looked at this problem by building on previous work in asking the question "What are the proper assumptions to be made about the micro equations? (p. 1)." They argue that there is improper information about the micro equations to properly specify them in practice, implying that in the specifics of this project, using aggregates will possibly be more accurate than the model built from the disaggregated values. For example, if the information available for the micro equations is insufficient to specify and estimate the proper model, using the aggregate macro equation will be more accurate Grunfeld and Griliches (1960) do not however conclusively state that the micro values are in general less accurate due to estimation.

Aigner and Goldfeld (1974) note that one of the major contentions of Grunfeld and Griliches's paper (1960) is that "the poor quality of micro data may be another source of aggregation gain (p. 10)". They make this the main focus of their work. They study a model where the both the aggregated and disaggregated values are measured with error, but the latter's smaller than the former's. The authors consider a two micro equation system and compare efficiency to the corresponding macro equation. They look at the case where the micro coefficients are constrained to be equal as well as the case where these coefficients are allowed to differ. Aigner and Goldfeld also consider what they call a "pseudo-aggregate" equation. This representation is analagous to the state's unemployment value formed by the aggregation of the county rate.

Their results lead to several conclusions. If one is willing to assume that the coefficients of the micro variables are equal, the most efficient estimation technique is the standard regression framework on using disaggregated data. If the researcher is not willing to make this assumption, it becomes more difficult to determine which technique is more efficient. If observation errors exist in the micro variables, it is likely that a system of macro variables will have a smaller mean square error. The accuracy of predictions depends on the assumption of equal coefficients on the micro equations. With this condition, the micro equation "always dominates the macro equation (p. 133)." The macro equation is less accurate if one removes this restriction. They do note however that there are situations in which macro equation can outperform the micro equation. If the circumstances exist that micro variables exhibit "exactly offsetting observation errors (p. 134)", the macro equation will provide better predictions. This holds even under equal micro coefficients. The authors also conclude that if the equality is relaxed, neither equation "yields a consistent forecast (p. 134)." Finally they find that after they remove the restriction of coefficient equality, the pseudo-aggregate equation provides consistent predictions. This model is analogous to building a state unemployment forecast by aggregating county values.

Granger (1987) also addresses an issue when aggregating components to build a macro level forecast. He notes that when analyzing data at the macro level, there may exist relationships between the variables that can be missed or underestimated at the micro level. It is feasible to think there are correlations between these county variables that could be found to be statistically insignificant when estimated using the components. However it is a possibility that after aggregation the factor causing the correlation could be found to be highly significant at the macro level. Granger (1987) continues by looking at common factors and individual factors. Common factors (CF) are those correlations that are present across most of the components and individual factors (IF) are unique to each individual county. He finds that "if a microvariable has a linear representation containing both CF's and IF's, then on aggregation only terms involving CF's will be of any relevance (p. 213)." The author concludes that these CF's are much more relevant in estimating micromodels. If a microvariable is causing error in the model, it could be the result of a common factor. This would be the case if the estimates of the variables are biased by something common across the sample. If these CF's are present, they can affect the final predictions in the resulting macromodel.

As easily seen from this section, aggregating components also brings issues that can lead to forecast error. While the procedure is still a subject of interest, it is apparent from the previous research that using this technique is a viable way to forecast unemployment values for the state based on county data.

More recently Giacomini and Granger (2004) integrated the aggregation issue and spatial correlation and measured the efficiency of various models. This research is similar to the work done by Elhorst (2001); however Giacomini and Granger's work also consider aggregate models. The authors set up the following four models with which to measure spatially correlated data:

1. A simple forecasting model to make predictions about the aggregate using only the aggregate's values
2. A univariate model of the components and using these results to build a prediction of the aggregate
3. A vector autoregressive (VAR) model using forecasts of the components and allowing for correlations between all of the disaggregated variables to make forecasts of the aggregate value
4. A space-time autoregressive model where intercomponent correlations are only considered between "neighbors" and these component estimates will again be used to make predictions of the aggregate

They first compare these four models when the parameters are known. They find that the VAR model (model 3) is more efficient than the model using the components and building aggregate forecasts (model 2). They find also that "VAR is (weakly) more efficient than the forecast based on the aggregated data (p. 14)", which is model 1. Giacomini and Granger (2004) go on to conclude that the space-time model (model 4) is just as efficient as the VAR model.

When making predictions using estimated parameters, they find different results. They find that the "space-time AR model is (weakly) more efficient than the aggregate of forecasts from a VAR (p. 17)." They also find that VAR is less efficient than the predictions built from the aggregate, provided the researcher is willing to pool the data. Pooling the data is appropriate if "total spatial influence is relatively uniform across regions (p.14)." Space-time AR models are in general more efficient than VAR under uncertainty. They continue to study this problem by setting up a Monte Carlo experiment. These results show that the space-time AR outperforms the other three models in terms of minimizing mean square errors, while the prediction build from the aggregate's values alone is the least efficient. Their main conclusion is that if spatial relationships exist between the components in a data set, ignoring these correlations can cause prediction error, regardless of the strength of the dependence.

Another recent forecasting model dealing with spatial correlation is highly similar to the one proposed in this research. Xavier de Luna and Marc Genton (2004) constructed a forecasting model for unemployment in the United States that takes into account the possibility of spatial dependence. The authors first divided the U.S. into nine regions, thereby building a spatial lattice. The method they use for building the weighting matrix is an ordering process based on distance. They first find the center of each respective region. The distance measure used is based first on common borders then on distance. For each component, the neighbor sharing an eastern border is given the value "1". They then continue counter-clockwise sequentially ordering the remaining neighbors who share a border. For those who are not touching the region in question, distances between the center points are used to finish the ordering. This procedure allows the authors to "enter our predictors sequentially in our model and stop whenever the partial correlation between z(s,t)[1] and a new predictor is zero, conditionally on all other predictors already in the model (p. 289)."

Genton and de Luna (2004) continue by putting together separate models for each region. After taking steps to remove seasonality in the data, they find that unemployment can be fit using autoregressive model. Their next stage consists of building the VAR model to fit the data more accurately and make predictions. By looking at the correlation coefficients between the divisions at temporal lags from t-1 to t-25, they can find which spatial dependences as well as which temporal lags are statistically significant.

The final step the authors take is to look at the residuals from the two models and determine which model is more effective. They find that "the VAR model with spatial structure captures the dependence structure of the data better, as it was expected (p. 297)." They conclude that spatial dependence is present in their data. They do this by noting that the VAR model considering regional correlations is more effective in making forecasts than the univariate model.

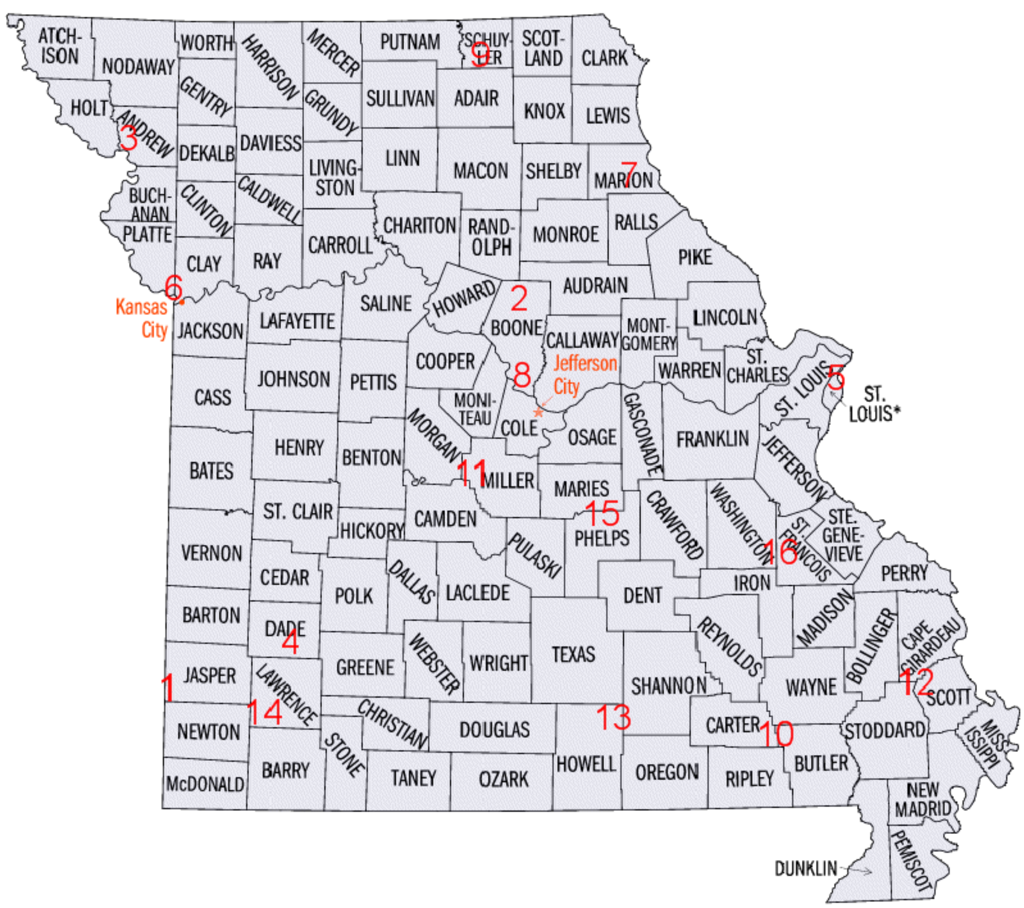
The research discussed above gives an idea of the situations that can arise when trying to use county unemployment values to predict the state's overall unemployment rate. From the presence and classification of spatial correlation to the problems of aggregating the forecasts, these authors give a synopsis of what kinds of circumstances will need consideration. Hopefully the preceding research will lead to a valid model that performs efficiently and accurately.

[1] z is defined as unemployment, and is a function of space and time

METHODOLOGY AND DATA

In this paper I attempt to build a model similar to the one Genton and de Luna estimate. I will compare two methods of forecasting monthly unemployment for sixteen metropolitan statistical areas (MSA) and local market areas (LMA) across the state of Missouri. The data is monthly data compiled from the Local Area Unemployment Statistics Archive (LAUS) from 1990-2000. These areas are Joplin (1), Columbia (2), St. Joseph (3), Springfield (4), St. Louis (5), Kansas City (6), Marion-Ralls (7), Cole-Callaway-Montieau (8), Adair-Schyler (9), Butler-Ripley-Carter (10), Camden-Miller (11), Cape Girardeau-Miller-New Madrid (12), Howell-Oregon-Shannon (13), Lawrence-Barry (14), Phelps-Maries (15), and St. Francois-Washington (16).

Figure 1. Missouri County Map



The approximate locations of the regions under study can be seen on the Missouri map. For some of the regions the data reaches back farther (as far as 1974), however much of this data is concentrated in the northern part of the state and no data exists for the southeast. In the hope of constructing a more complete statewide picture, I included the extra regions while sacrificing the length of the data set. To build the model to make predictions as accurate as possible, I will first-difference[2] the data to remove any trend component as well as twelfth-difference[3] the data to remove seasonality.

The first model I will estimate is a simple univariate autoregressive model of each region. For each of the sixteen areas, a separate model will attempt to make predictions about each statistical area[4]. The model to be estimated is:

$$Y_t = \beta_0 + \sum_{i=1}^{p} (\alpha_i Y_{t-i}) + v_t$$

This is a classic representation of an AR(p) process, where the magnitude of p will be decided using AIC criterion. Since each area is being estimated separately, it is not necessary that the length of the lag for to be the same for each region. While it seems likely that for regions of similar demographic and economic makeup, as well as those which are geographically closer, the lags will be similar, though it is not a requirement of the model.

To estimate the AR(p), the temporal lags of the value will be introduced to the model as predictors. Using AIC, I will attempt to determine the persistence of the temporal correlation in order to estimate p. Once p has been established, it is then possible to use the constructed model to make predictions about the future values of

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[2] First-difference graphs are displayed in Appendix D
[3] First and twelfth-difference graphs are displayed in Appendix E
[4] Plots of each series for each region are found in Appendix C

unemployment in each respective region. These forecasts can be compared to observed values to measure their accuracy and then compared to the accuracy of the second model.

The second model will be a system of simultaneous equations where the current value of each region will be predicted by not only historic values of that respective region but also the past of other regions across the state. More formally, the specification of this model is:

$$Y_t = \beta_0 + \sum_{i=1}^{p} (\alpha_i Y_{t-i}) + \sum_{j=1}^{k} \sum_{l=1}^{m} (\alpha_{j,l} X_{j,t-l}) + v_t$$

In this equation, the first half is the AR(p) model for the region. The second half is the portion that accounts for spatial dependence. The first summation indexes each of the regions while the second indexes the lag of the regions. If we consider Joplin as Y_t and $j = 1$ and $l = 3$, then $X_{1,t-3}$ is the third temporal lag of the first neighbor which for Joplin is Springfield.

The process for introducing the neighbors into the simultaneous equation model is more complicated than for the AR(p) case. To achieve this feat, each region will initially use its first temporal lag as its first predictor. The second predictor will be the first temporal lag of what is classified as its first spatial lag. In this context, spatial lag refers to the neighbors of the region under study. The first spatial lag is the first neighboring region introduced to the model in accordance with the ordering matrix found in Appendix A. After each of the first temporal lags of the spatial lags is introduced, the process repeats for each of the 24 temporal lags[5]. This implies that I will consider historic unemployment for up to two years prior to the current period. This is the procedure

[5] Graphical representation of the introduction process is shown in Appendix B

followed by de Luna and Genton (2004) in building their model for the United States using the nine census regions as the components.

The order of the introduction of the spatial neighbors will vary depending on the positioning of the region. For those that are centrally located within the state, I follow an exploding spiraling motion that moves in a clockwise direction. The regions are introduced to the model in this fashion. For those regions located closer to the borders of the state where a spiral is less practical, I use a back and forth sweeping motion to construct the ordering process. The specific ordering for the regions in this paper is found in Appendix A. The final step will be removing any predictors that prove to be insignificant. For example, assume the model chosen uses the first temporal lag of all sixteen regions and the second lag of regions one through eight. If the second temporal lag of the fifth region is found to be insignificant, it will be removed. This procedure is in the spirit of Elhorst (2001) by finding a larger and more general model and making it more specific while serving two purposes. First, it will help to decrease the number of predictors in the model increasing the degrees of freedom in the model. Second, it will remove any unimportant predictors that are statistically insignificant and add no predictive power to the model.

After building these two models, the next step is to use them to construct forecasts of unemployment for each region. Since I am using data from 1990-2000, this allows me to use the data from 2001-2004 to measure the accuracy of the predictions for each model. Since the data is monthly, it is natural to make one-month predictions for the areas' unemployment. However it is often difficult to implement policy in a short time frame, particularly since some data is reported late in the month or in the succeeding period. For this reason, I will also construct forecasts that will predict unemployment for the following year. For example, data that ends in January of 2000 will be used to forecast the value for January of 2001. This prediction of next year's unemployment (if sufficiently accurate) allows time to confidently compile the necessary data as well as time to make preparations based on the predictions. Once the forecasts are made, I will compare the accuracy of the two models.

RESULTS

Estimation of AR Models

Using the Bayesian Information Criterion (BIC), a separate univarate autoregressive model was estimated for each of the sixteen regions. The models were tested from temporal lags one to twenty-four to determine which would be the most accurate predictor of unemployment. Appendix F shows the resulting BIC estimates for the areas. In each of the twenty-four models, the most accurate predictor is the AR(24). This is not a surprising result given the fact that the model uses monthly data. It is likely that when forecasting January 2000 for example that January of 1999 and of 1998 would be strong predictors. The strength of the twelfth lag and twenty-fourth lag is evident not only in the BIC estimates but also in the autocorrelation and partial autocorrelation functions[6]. In most cases, introducing these lags brings a significant decrease in the BIC values indicating these are important variables to include in the model.

Estimation of Spatial Models

Using the methodology described before and once again the BIC, spatial models were also estimated for each region. Because of the way the BIC's were estimated, the order of introduction is trivial. Using RATS, I calculated BIC's for every possible (given the data) permutation of spatial and temporal lags. The results of this estimation are the following models:

Table 1. Spatial Models

Adair-Schuyler	Y(1){1-3} Y(2){1-2} Y(3){1-12} Y(4){1-2}
Butler-Ripley	Y(1){1-12} Y(2){1-2} Y(3){1}
Camden-Miller	Y(1){1} Y(2){1-12} Y(3){2} Y(4){1}
Cape G.-Scott-N. Madrid	Y(1){1-12} Y(2){1} Y(3){1} Y(4){1-2}
Cole-Callaway-Montieau	Y(1){1-12} Y(2){1-3}
Columbia	Y(1){1} Y(2){1-2} Y(3){12}
Howell-Oregon-Shannon	Y(1){1-12} Y(2){1}
Joplin	Y(1){1-12} Y(2){1}
Kansas City	Y(1){1-12} Y(2){1}
Lawrence-Berry	Y(1){1} Y(2){2} Y(3){1-12} Y(4-16){1}
Maries-Phelps	Y(1){1} Y(2){1} Y(3){1-12} Y(4-11){1}
Marion-Ralls	Y(1){1-12} Y(2){1}
Springfield	Y(1){1-12} Y(2){1}
St. Joseph	Y(1){1-12} Y(2){1}
St. Louis	Y(1){1} Y(2){1-11} Y(3-5){1}
St. Francois-Washington	Y(1){1-3} Y(2){1} Y(3){1-12} Y(4-7){1}

To explain what this notation means, look at Columbia's equation. The Y(1){1} refers to region one and lag one. This implies that Columbia's first temporal lag is included in the model. Y(2){1-2} refers to region two and lags one through two. This indicates that Cole-Callaway-Montieau's[7] first and second temporal lags are included. The final predictor is the twelfth temporal lag of Maries-Phelps.

There are data restrictions on the process of selecting the appropriate spatial model that are worth making clear. The data available for these regions is monthly data from 1990-2004. In order to compare the accuracy of forecasting, I truncate the data at December of 2000. The data post-December 2000 is used to evaluate forecast accuracy. After removing seasonality and trend, the dataset contains 107 observations. Because I am using both temporal and spatial lags, it is impossible to estimate the BIC of every possible model given the lack of observations. The BIC's estimated above are the lowest of those spatial models that are feasible due to data restrictions.

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[6] Plots are found on Appendix G & H

Another outcome of the data restrictions is the inability to estimate border effects. For example, St. Louis's city limits borders the state of Illinois, so it is reasonable to hypothesize that there are MSA's or LMA's in Illinois that would affect the unemployment of the St. Louis MSA. This issue is similar for any other region located near the border of Missouri. Because the data was unavailable to properly estimate the border effects, they are omitted from this paper.

It is important to more carefully look at six of the models selected using BIC. Note that the regions of Howell-Oregon-Shannon, Joplin, Kansas City, Marion-Ralls, Springfield, and St. Joseph are all specified by the same equation. In the cases of these areas, the lowest BIC was the AR(12) process. However for the purposes of this research, I selected the spatial model with the lowest BIC for comparison purposes. The most accurate AR model in terms of BIC is AR(24) for these regions, so using AR(12) to compare forecast accuracy would not give insight about whether univariate AR or a spatial model is a better overall predictor.

Residual Analysis

One way to determine if the spatial models are capturing the dependence between the regions is to look at the residuals from both models. If the spatial equation is effectively modeling the correlations between the MSA/LMA's then we should find evidence of that in a correlation matrix. We can compare the residuals of the AR(24) to those of the spatial models and should see smaller coefficients for the latter. The following tables[8] are the variance/covariance matrices[9] for the first lag of both the AR(24) and the spatial specifications.

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[7] Matrix of ordering is found in Appendix A
[8] R(1) through R(16) refer to the regions under study in alphabetical order

Table 2. AR Residuals with One Lag

Lag 1, AR	R(1)	R(2)	R(3)	R(4)	R(5)	R(6)	R(7)	R(8)
R(1)	0.7399	**0.438*** **	**0.0957**	**0.1695***	**0.365*** **	**0.2457*** **	**0.2984*** **	**0.3097*** **
R(2)	0.2033	0.2912	**0.1546**	**-0.026**	**0.3121*** **	**0.3031*** **	**0.3274*** **	**0.4443*** **
R(3)	0.0653	0.0662	0.6299	**0.0942**	**0.1555**	**0.3297*** **	**0.1244**	**0.0489**
R(4)	0.0472	-0.004	0.0242	0.1051	**0.0211**	**0.2472*** **	**0.1998** **	**0.1784***
R(5)	0.0679	0.0364	0.0267	0.0015	0.0467	**0.4423*** **	**0.5074*** **	**0.0129**
R(6)	0.0898	0.0695	0.1112	0.034	0.0406	0.1805	**0.6649*** **	**0.1554**
R(7)	0.1725	0.1188	0.0664	0.0435	0.0737	0.1899	0.452	**0.1961** **
R(8)	0.0745	0.067	0.0108	0.0162	0.0008	0.0185	0.0369	0.0781
R(9)	0.1447	0.0785	0.0566	0.0115	0.0556	0.0716	0.1337	0.0247
R(10)	0.2114	0.0842	0.1609	0.0547	0.02	0.1707	0.2788	0.0631
R(11)	0.0444	0.0587	0.0447	-0.002	0.036	0.0736	0.1248	0.0002
R(12)	0.0759	0.0434	0.0725	0.0269	0.0364	0.0598	0.0585	0.0026
R(13)	-0.006	-0.005	0.0621	0.0357	0.0326	0.1005	0.1643	0.0148
R(14)	0.0691	0.0583	-0.004	0.0329	0.0556	0.0939	0.1915	0.0239
R(15)	0.0197	0.043	0.1752	0.0451	0.0647	0.1213	0.1455	-0.007
R(16)	0.1054	0.0638	0.0981	-0.005	0.0609	0.0665	0.1006	0.0186

Lag 1, AR	R(9)	R(10)	R(11)	R(12)	R(13)	R(14)	R(15)	R(16)
R(1)	**0.3604*** **	**0.2421** **	**0.1719**	**0.2067** **	**-0.012**	**0.1307**	**0.0389**	**0.2565*** **
R(2)	**0.3115*** **	**0.1537**	**0.3621*** **	**0.1885** **	**-0.016**	**0.1758** **	**0.1355**	**0.2473*** **
R(3)	**0.1526**	**0.1997** **	**0.1875** **	**0.214** **	**0.1467**	**-0.008**	**0.3751*** **	**0.2587*** **
R(4)	**0.0762**	**0.1663***	**-0.018**	**0.1947** **	**0.2062** **	**0.1652** **	**0.2367** **	**-0.033**
R(5)	**0.5511*** **	**0.0911**	**0.5543*** **	**0.3949*** **	**0.2825*** **	**0.4184*** **	**0.5085*** **	**0.5896*** **
R(6)	**0.3608*** **	**0.3957*** **	**0.5769*** **	**0.3297*** **	**0.4434*** **	**0.3594*** **	**0.485*** **	**0.3279*** **
R(7)	**0.4258*** **	**0.4085*** **	**0.6182*** **	**0.2038** **	**0.4582*** **	**0.4632*** **	**0.3678*** **	**0.3133*** **
R(8)	**0.1896** **	**0.2224** **	**0.0023**	**0.022**	**0.0995**	**0.1389**	**-0.042**	**0.1392**
R(9)	0.218	**0.1054**	**0.3804*** **	**0.287*** **	**0.2297** **	**0.3053*** **	**0.2827*** **	**0.4611*** **
R(10)	0.0499	1.0308	**0.2934*** **	**0.1014**	**0.4041*** **	**0.1885** **	**0.191** **	**0.1745***
R(11)	0.0533	0.0894	0.0901	**0.339*** **	**0.5299*** **	**0.3424*** **	**0.4786*** **	**0.4853*** **
R(12)	0.0572	0.0439	0.0435	0.1823	**0.3066*** **	**0.3116*** **	**0.27*** **	**0.4801*** **
R(13)	0.0572	0.2189	0.0849	0.0698	0.2846	**0.4034*** **	**0.3062*** **	**0.2974*** **
R(14)	0.0877	0.1177	0.0632	0.0818	0.1323	0.3781	**0.3461*** **	**0.4263*** **
R(15)	0.0777	0.1141	0.0846	0.0678	0.0961	0.1252	0.3464	**0.5208*** **
R(16)	0.1028	0.0846	0.0696	0.0979	0.0758	0.1252	0.1464	0.2282

*10% Significance
**5% Significance
***1% Significance

[9] Numbers in boldface type are correlation coefficients

Table 3. Spatial Residuals with One Lag

Lag 1, Spatial	R(1)	R(2)	R(3)	R(4)	R(5)	R(6)	R(7)	R(8)
R(1)	0.3407	0.0633	0.2255**	0.2458***	0.1857**	0.3125***	0.0266	-0.042
R(2)	0.0148	0.1594	0.3472***	0.3705***	0.3732***	0.4173***	0.3187***	0.1773*
R(3)	0.0567	0.0598	0.1859	0.2601***	0.4483***	0.3172***	0.3497***	0.0876
R(4)	0.0434	0.0448	0.0339	0.0916	0.2909***	0.3793***	0.2691***	0.3451***
R(5)	0.0316	0.0434	0.0563	0.0257	0.0849	0.4268***	0.2488***	0.2039**
R(6)	0.0335	0.0306	0.0252	0.0211	0.0229	0.0338	0.1812*	0.2103**
R(7)	0.0074	0.0603	0.0714	0.0386	0.0343	0.0158	0.2246	0.2314**
R(8)	-0.009	0.0246	0.0131	0.0363	0.0206	0.0134	0.0381	0.1206
R(9)	-0.038	0.0038	-0.008	-0.016	0.0019	-0.007	0.0108	0.0018
R(10)	-0.021	0.0102	3E-05	0.0188	0.0058	0.003	0.0262	0.0202
R(11)	0.0031	0.0284	0.0486	0.0257	0.0311	0.0129	0.0184	0.0167
R(12)	0.0809	0.0003	0.0292	0.0121	0.0277	0.0216	0.0038	0.0023
R(13)	0.0192	0.0249	0.0405	0.0192	0.0172	0.0159	0.0246	0.0224
R(14)	0.0363	0.064	0.043	0.0224	0.0833	0.0295	0.0217	0.0463
R(15)	0.0088	-0.009	0.0032	0.0088	0.0046	-0.002	0.0097	-0.006
R(16)	0.1027	-0.018	0.0392	0.0068	0.0182	0.0016	0.0295	-0.007

Lag 1, Spatial	R(9)	R(10)	R(11)	R(12)	R(13)	R(14)	R(15)	R(16)
R(1)	-0.302***	-0.125	0.0188	0.3725***	0.1593	0.1066	0.072	0.2954***
R(2)	0.0438	0.0906	0.2551***	0.0018	0.3022***	0.2745***	-0.104	-0.074
R(3)	-0.091	0.0003	0.4038***	0.1818*	0.4554***	0.1708*	0.0347	0.1525
R(4)	-0.251***	0.2194**	0.3046***	0.107	0.3085***	0.127	0.1379	0.0377
R(5)	0.0302	0.0698	0.3821***	0.2551***	0.2869***	0.4898***	0.0742	0.1048
R(6)	-0.179*	0.057	0.2512***	0.316***	0.419***	0.2744***	-0.058	0.0143
R(7)	0.1048	0.1949**	0.1392	0.0217	0.2521***	0.0783	0.0973	0.1046
R(8)	0.0243	0.2054**	0.1723*	0.0182	0.3135***	0.2283**	-0.086	-0.034
R(9)	0.0469	-0.019	0.0749	0.0061	-0.071	0.0589	0.0668	-0.046
R(10)	-0.001	0.0802	0.0983	-0.196	0.2479***	0.0442	-0.087	0.1232
R(11)	0.0045	0.0078	0.0778	0.0226	0.2988***	0.1032	0.0724	0.0567
R(12)	0.0005	-0.021	0.0023	0.1385	0.068	0.167	0.2222**	0.2008**
R(13)	-0.003	0.0145	0.0172	0.0052	0.0424	0.1575	-0.242**	0.1105
R(14)	0.0074	0.0073	0.0168	0.0363	0.0189	0.3407	0.0046	0.0395
R(15)	0.003	-0.005	0.0043	0.0174	-0.01	0.0006	0.0443	0.0136
R(16)	-0.006	0.0208	0.0094	0.0445	0.0136	0.0137	0.0017	0.355

*10% Significance
**5% Significance
***1% Significance

The tables for the first lag show strong evidence that the spatial models are capturing correlations between the regions effectively. The AR(24) model has a significantly larger number of correlations that pass at α=.01, implying that there is dependence present. The low number of significant correlation coefficients in the spatial model infers it is successful in modeling spatial dependence.

Forecasting Unemployment

Once the models have been estimated, I can then use RATS to calculate forecasts of unemployment based on both the AR models and the spatial models. Mean square forecast error (MFSE) is the selected measure of accuracy of the predictions. The following chart shows the values of MFSE for each region using either method and considering both one period ahead and twelve period ahead forecasts:

Table 4. One-period Forecasts

One period forecasts	AR(24)	Spatial Model	Ratio[10]
Adair-Schuyler	**0.427794646**	0.664743672	0.643548
Butler-Ripley	0.972715086	**0.885053235**	0.909879
Camden-Miller	**0.263981227**	0.341914075	0.772069
Cape Girardeau-Scott-New Madrid	**0.116475938**	0.140171228	0.830955
Cole-Callaway-Montieau	**0.091269709**	0.097266524	0.938347
Columbia	**0.021087023**	0.029310385	0.719439
Howell-Oregon-Shannon	**0.195517547**	0.201417196	0.970709
Joplin	0.096191797	**0.08642863**	0.898503
Kansas City	0.069640275	**0.065671706**	0.943013
Lawrence-Berry	**0.084265283**	0.164228792	0.513097
Maries-Phelps	**0.068536856**	0.127199484	0.538814
Marion-Ralls	0.147842944	**0.146426095**	0.990417
Springfield	**0.038663187**	0.040355042	0.958076
St.Joseph	**0.149892159**	0.150775309	0.994143
St. Louis	**0.085553521**	0.105373262	0.811909
St. Francois-Washington	**0.363129283**	0.887911995	0.40897

[10] Ratio is constructed by more accurate: less accurate. For example, if the ratio is .977, this implies that the MSFE of the more accurate is 97.7% of the MSFE of the less accurate

Table 5. Twelve-period Forecasts

Twelve period forecasts	AR(24)	Spatial Model	Ratio
Adair-Schuyler	0.631743513	**0.61744418**	0.977365
Butler-Ripley	3.398365045	**1.785040525**	0.525265
Camden-Miller	**0.290752126**	0.308688101	0.941896
Cape Girardeau-Scott-New Madrid	0.126220462	**0.113561948**	0.899711
Cole-Callaway-Montieau	0.208534518	**0.174259403**	0.835638
Columbia	**0.032425948**	0.034771725	0.932538
Howell-Oregon-Shannon	**0.24672178**	0.357312388	0.690493
Joplin	**0.104443525**	0.106325434	0.9823
Kansas City	0.084792869	**0.066288318**	0.781768
Lawrence-Berry	**0.122941945**	0.204973778	0.599794
Maries-Phelps	**0.087978091**	0.111650756	0.787976
Marion-Ralls	0.241378834	**0.217092516**	0.899385
Springfield	0.053293757	**0.050365543**	0.945055
St.Joseph	0.21644928	**0.207251083**	0.957504
St. Louis	0.139312371	**0.113391506**	0.813937
St. Francois-Washington	**0.507478364**	0.761019949	0.66684

As the table illustrates, the AR(24) formulation is a more accurate model in all but four cases when predicting one period into the future. Only Butler-Ripley, Joplin, Kansas City, and Marion-Ralls have spatial models that perform more effectively that their corresponding autoregressive model. However when predicting one year ahead (i.e. predicting January 2000's value based on data up to January 1999) the situation changes. In this framework, nine of sixteen spatial models outperform their AR counterparts.

CONCLUSIONS AND FUTURE RESEARCH

At this point, it is necessary to figure out how the AR could have proven so effective in forecasting when compared to the spatial model particularly in the case of one period forecasts. While the spatial model does appear more accurate in the 12 month forecasts, the AR(24) does exhibit strength in the shorter time frame. Most of the literature concludes the spatial model should be more effective, however in this particular experiment that hypothesis did not conclusively hold in the shorter time frame. In the longer horizon, however, the spatial model was more accurate in over half of the models. These results are encouraging given how strong the AR forecasts generally are. This outcome exhibits the idea that spatial models could be useful in forecasting unemployment.

One possibility is that there are spatial models that are more effective that cannot be properly estimated given the limitations of the data. I was not able to estimate every permutationally possible model due to the fact that the data consists of only 108 observations after transformation to remove trend and seasonality. It is plausible that a better predictive model exists given these sixteen regions that contains too many regressors to estimate. With more data points, I could find that there is a spatial model for every region that predicts more accurately than the corresponding autoregressive equation.

Given that the spatial model performs better in the longer horizon, it is possible that unemployment does not travel well. If unemployment increases in one of the regions, one month may not be a sufficient time frame to have an effect in any other area other than Y(1), especially considering the distance between some of these regions. If

Adair-Schuyler (which is far from other areas in this study) experiences a shock which causes their unemployment rate to increase, it is reasonable to imagine that it will take some time for the effects of their local shock to spread to other regions. They are simply too far away from anyone else in this sample for the ramifications of their shock to affect the unemployment of the others. Note that the four spatial models that were found more effective in the 1 month forecast are Joplin, Kansas City, Marion-Ralls, and Butler-Ripley. Each of these models contains its own temporal lags from one to twelve. The presence of the twelfth lag in these models further exhibits the possibility that unemployment shocks take some time to spread across regions.

Another theory is that the regions are geographically far enough apart that the spatial component is not strong enough to affect the home region's unemployment. Only a few groups in this sample of regions could be considered border-sharing areas. LMA's such as Adair-Schuyler, Howell-Oregon-Shannon, and Maries-Phelps are a significant geographical distance from all others in the state. Stetzer (1982) noted how the strengths of the correlations decay with increasing distance. Based on this fact, looking at a more condensed group of zones (i.e. counties in a state, states in a nation) could result in the spatial model producing better forecasts than the AR(24). Using border-sharing regions would also allow us to see if the distance between the regions was a factor in the spatial models being more accurate than the autoregressive models in the one year forecasts. If spatial models are more accurate in the shorter time horizon where the areas are more geographically condensed, this could be evidence that unemployment takes some time to travel.

One approach that follows naturally from this paper is building spatial models for counties in a state. It is possible to construct a separate spatial model for each county in the state of Missouri and determine if their respective spatial models perform better than a simple autoregressive procedure. This would more closely represent the study done by Genton and de Luna (2004) who used the nine census divisions each which shares a border with at least one other. Another extension of this would be to not only build county-level forecasts but also use those predictions to construct an aggregate level of unemployment for the state. This aggregated model built from county data could be compared to a state AR(p) model to further compare the two methods.

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Appendix A

Matrix of Ordering

Joplin	Columbia	St. Joseph
Springfield	Cole-Callaway-Montieau	Kansas City
Lawrence-Barry	Maries-Phelps	Joplin
Kansas City	Camden-Miller	Lawrence-Barry
St. Joseph	Marion-Ralls	Springfield
Camden-Miller	St. Louis	Camden-Miller
Howell-Oregon-Shannon	St. Francois-Washington	Howell-Oregon-Shannon
Maries-Phelps	Howell-Oregon-Shannon	Maries-Phelps
Cole-Callaway-Montieau	Lawrence-Barry	Cole-Callaway-Montieau
Columbia	Springfield	Columbia
Adair-Schuyler	Kansas City	Adair-Schuyler
Marion-Ralls	Adair-Schuyler	Marion-Ralls
St. Francois-Washington	Cape G.-Scott-New Madrid	St. Francois-Washington
Butler-Ripley	Butler-Ripley	Butler-Ripley
Cape G.-Scott-New Madrid	Joplin	Cape G.-Scott-New Madrid
St. Louis	St. Joseph	St. Louis

Springfield	St. Louis	Kansas City
Lawrence-Barry	St. Francois-Washington	Joplin
Joplin	Cape G.-Scott-New Madrid	St. Joseph
Camden-Miller	Butler-Ripley	Lawrence-Barry
Maries-Phelps	Marion-Ralls	Springfield
Howell-Oregon-Shannon	Adair-Schuyler	Camden-Miller
Kansas City	Columbia	Howell-Oregon-Shannon
Cole-Callaway-Montieau	Cole-Callaway-Montieau	Maries-Phelps
Columbia	Maries-Phelps	Cole-Callaway-Montieau
St. Francois-Washington	Howell-Oregon-Shannon	Columbia
Butler-Ripley	Camden-Miller	Adair-Schuyler
St. Joseph	Springfield	Marion-Ralls
Adair-Schuyler	Lawrence-Barry	St. Francois-Washington
Marion-Ralls	Joplin	Butler-Ripley
St. Louis	Kansas City	Cape G.-Scott-New Madrid
Cape G.-Scott-New Madrid	St. Joseph	St. Louis

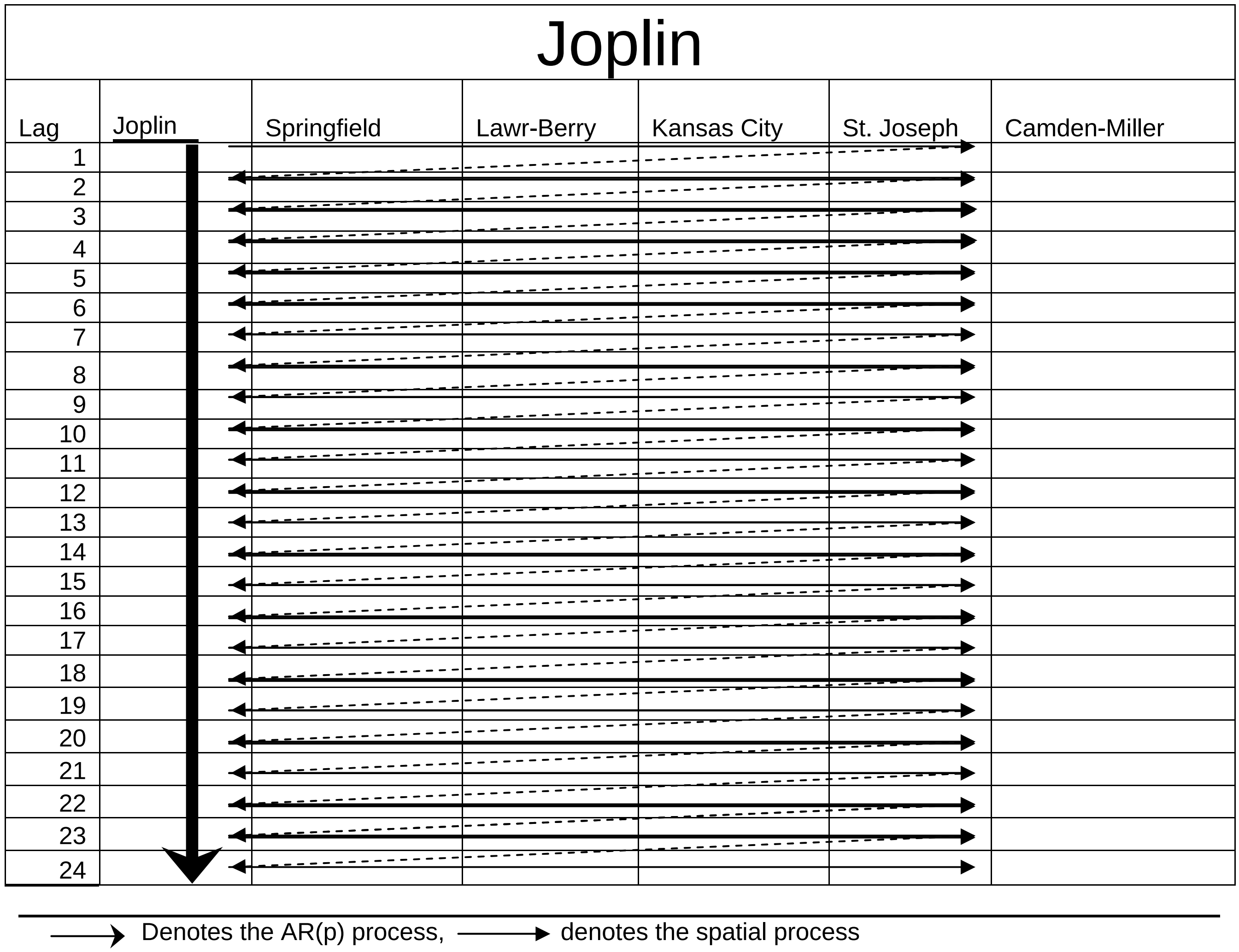
Marion-Ralls	Cole-Callaway-Montieau	Adair-Schuyler
Columbia	Columbia	Marion-Ralls
Adair-Schuyler	Maries-Phelps	St. Joseph
St. Louis	Camden-Miller	Kansas City
Cole-Callaway-Montieau	Marion-Ralls	Columbia
Camden-Miller	St. Louis	Cole-Callaway-Montieau
St. Francois-Washington	St. Francois-Washington	Camden-Miller
Maries-Phelps	Adair-Schuyler	St. Louis
Kansas City	Cape G.-Scott-New Madrid	Maries-Phelps
St. Joseph	Butler-Ripley	St. Francois-Washington
Cape G.-Scott-New Madrid	Howell-Oregon-Shannon	Springfield
Butler-Ripley	Springfield	Joplin
Howell-Oregon-Shannon	Kansas City	Lawrence-Barry
Lawrence-Barry	Lawrence-Barry	Howell-Oregon-Shannon
Springfield	Joplin	Butler-Ripley
Joplin	St. Joseph	Cape G.-Scott-New Madrid

Butler-Ripley	Camden-Miller	Cape G.-Scott-New Madrid
Cape G.-Scott-New Madrid	Cole-Callaway-Montieau	Butler-Ripley
Howell-Oregon-Shannon	Maries-Phelps	St. Francois-Washington
St. Francois-Washington	Columbia	St. Louis
Lawrence-Barry	Marion-Ralls	Maries-Phelps
Camden-Miller	St. Louis	Howell-Oregon-Shannon
Springfield	St. Francois-Washington	Camden-Miller
Joplin	Howell-Oregon-Shannon	Cole-Callaway-Montieau
Maries-Phelps	Springfield	Columbia
St. Louis	Kansas City	Marion-Ralls
Cole-Callaway-Montieau	Adair-Schuyler	Springfield
Columbia	Cape G.-Scott-New Madrid	Lawrence-Barry
Marion-Ralls	Butler-Ripley	Joplin
Kansas City	Lawrence-Barry	Adair-Schuyler
St. Joseph	Joplin	Kansas City
Adair-Schuyler	St. Joseph	St. Joseph

Howell-Oregon-Shannon	Lawrence-Barry	Maries-Phelps	St. Francois-Washington
Butler-Ripley	Joplin	St. Francois-Washington	Cape G.-Scott-New Madrid
Cape G.-Scott-New Madrid	Springfield	Camden-Miller	Butler-Ripley
Lawrence-Barry	Kansas City	Cole-Callaway-Montieau	Howell-Oregon-Shannon
Joplin	Camden-Miller	St. Louis	Maries-Phelps
Springfield	Howell-Oregon-Shannon	Cape G.-Scott-New Madrid	St. Louis
Maries-Phelps	Butler-Ripley	Butler-Ripley	Lawrence-Barry
St. Francois-Washington	Maries-Phelps	Howell-Oregon-Shannon	Springfield
Camden-Miller	Cole-Callaway-Montieau	Springfield	Camden-Miller
Cole-Callaway-Montieau	St. Joseph	Columbia	Cole-Callaway-Montieau
St. Louis	Columbia	Lawrence-Barry	Joplin
Columbia	St. Francois-Washington	Joplin	Columbia
Kansas City	Cape G.-Scott-New Madrid	Kansas City	Kansas City
Marion-Ralls	St. Louis	Marion-Ralls	Marion-Ralls
Adair-Schuyler	Marion-Ralls	St. Joseph	St. Joseph
St. Joseph	Adair-Schuyler	Adair-Schuyler	Adair-Schuyler

Appendix B

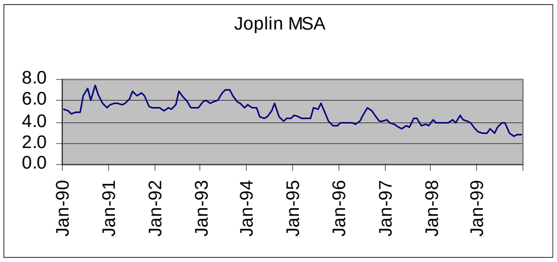
AR(p) vs. Spatial

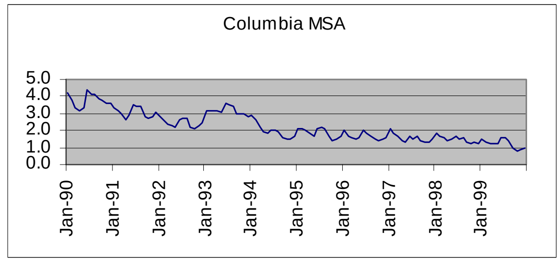


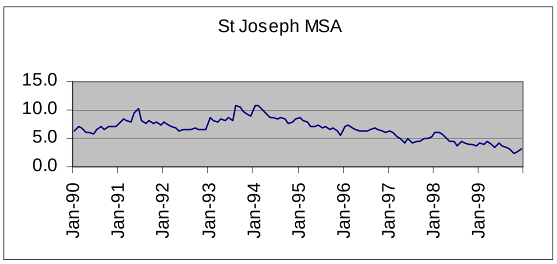
This illustrates graphically how the temporal lags will be injected into the AR(p) model as well as how the neighbors' lags will be introduced to the spatial model. The AR(p) model will inject temporal lags only as indicated by the downward arrow. The spatial model will introduce the first temporal lag of the region (here, Joplin) followed by the first temporal lag of its first neighbor (Springfield) followed by the first temporal lag of its second neighbor (Lawrence-Berry) until all first temporal lags of all neighbors are considered. It next moves to the second temporal lag of the region (Joplin) followed by the second temporal lags in order of each of its neighbors. This process continues for all twenty-four temporal lags.

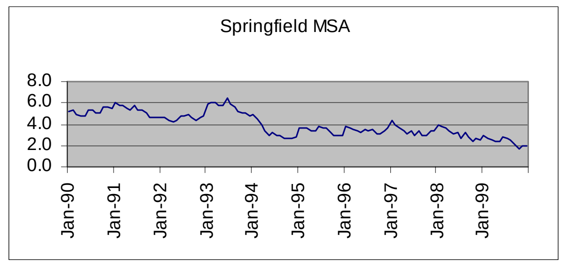
Appendix C

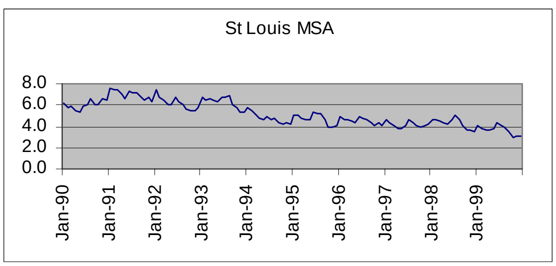
Unemployment Rates of Regions

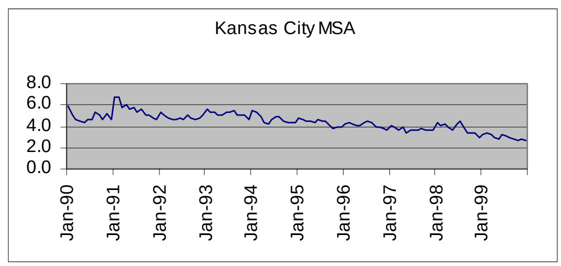


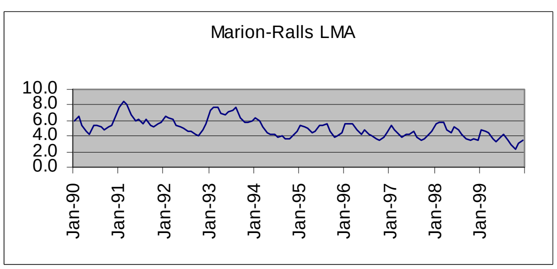


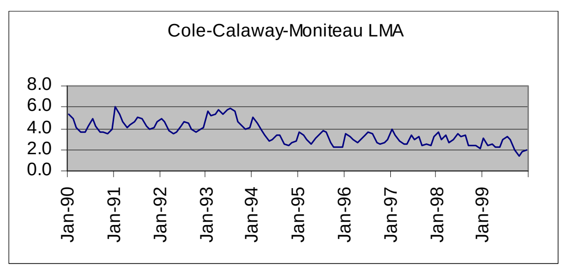


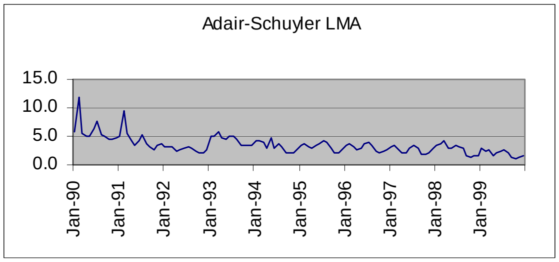


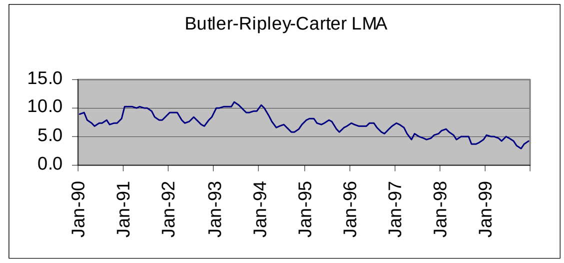


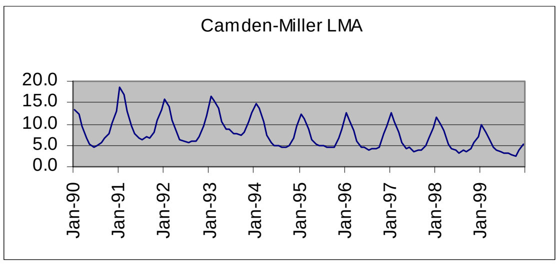


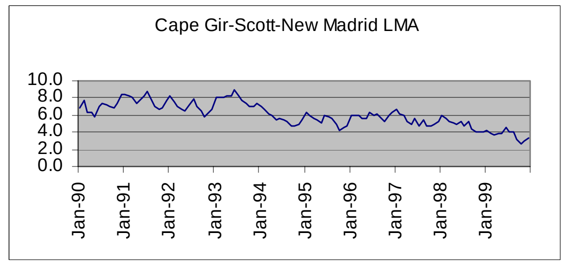


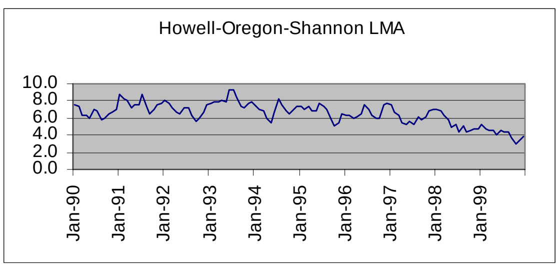


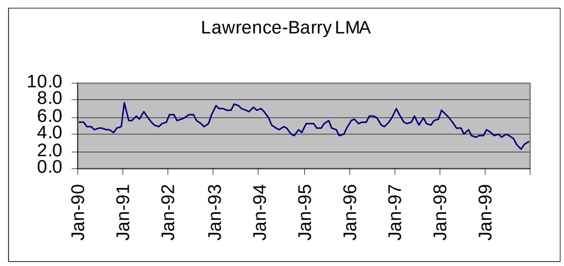

Adair-Schuyler LMA
15.0
10.0
5.0
0.0
Jan-90
Jan-91
Jan-92
Jan-93
Jan-94
Jan-95
Jan-96
Jan-97
Jan-98
Jan-99

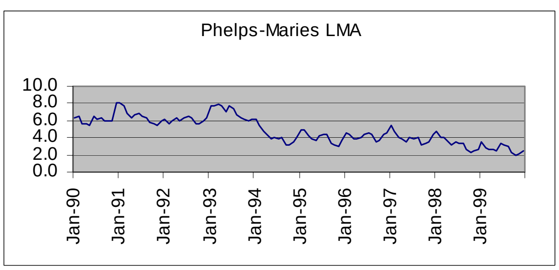

Butler-Ripley-Carter LMA
15.0
10.0
5.0
0.0
Jan-90
Jan-91
Jan-92
Jan-93
Jan-94
Jan-95
Jan-96
Jan-97
Jan-98
Jan-99

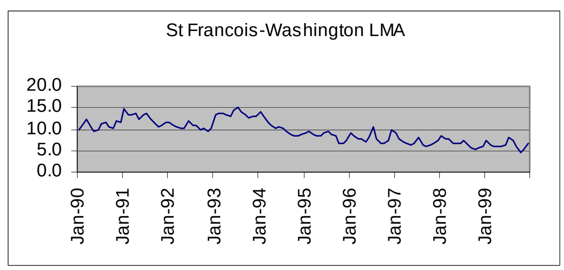

Camden-Miller LMA
20.0
15.0
10.0
5.0
0.0
Jan-90
Jan-91
Jan-92
Jan-93
Jan-94
Jan-95
Jan-96
Jan-97
Jan-98
Jan-99


Cape Gir-Scott-New Madrid LMA
10.0
8.0
6.0
4.0
2.0
0.0
Jan-90
Jan-91
Jan-92
Jan-93
Jan-94
Jan-95
Jan-96
Jan-97
Jan-98
Jan-99


Howell-Oregon-Shannon LMA
10.0
8.0
6.0
4.0
2.0
0.0
Jan-90
Jan-91
Jan-92
Jan-93
Jan-94
Jan-95
Jan-96
Jan-97
Jan-98
Jan-99

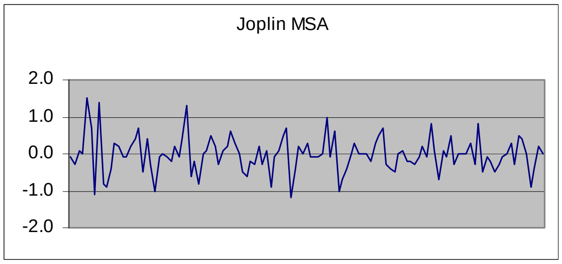

Lawrence-Barry LMA
10.0
8.0
6.0
4.0
2.0
0.0
Jan-90
Jan-91
Jan-92
Jan-93
Jan-94
Jan-95
Jan-96
Jan-97
Jan-98
Jan-99

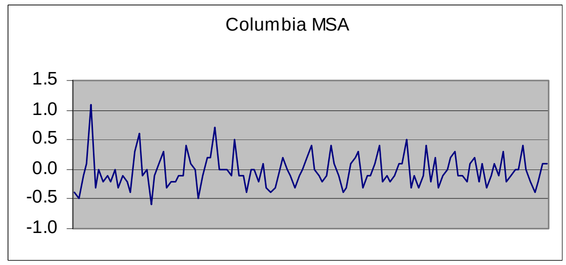

Phelps-Maries LMA
10.0
8.0
6.0
4.0
2.0
0.0
Jan-90
Jan-91
Jan-92
Jan-93
Jan-94
Jan-95
Jan-96
Jan-97
Jan-98
Jan-99

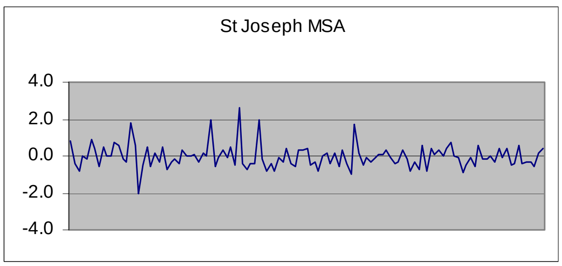

St Francois-Washington LMA
20.0
15.0
10.0
5.0
0.0
Jan-90
Jan-91
Jan-92
Jan-93
Jan-94
Jan-95
Jan-96
Jan-97
Jan-98
Jan-99

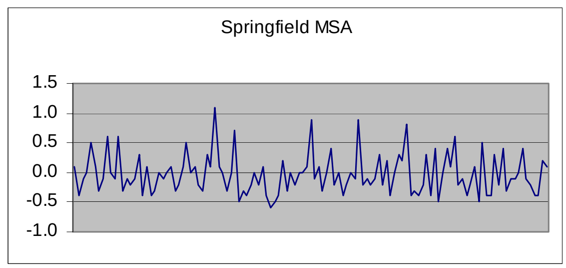
Appendix D

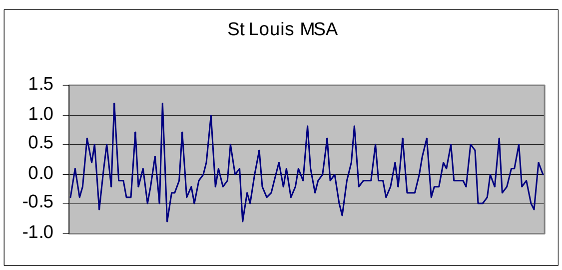
First Difference of Unemployment

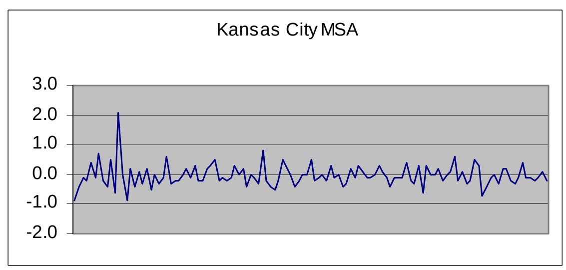


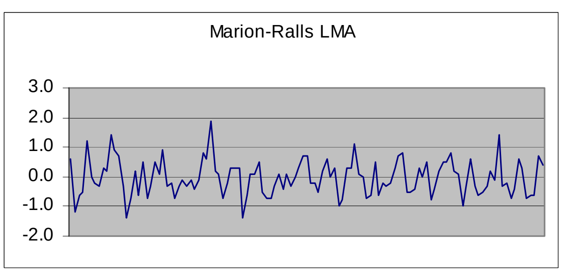


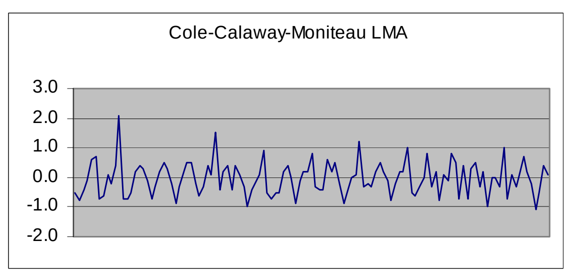


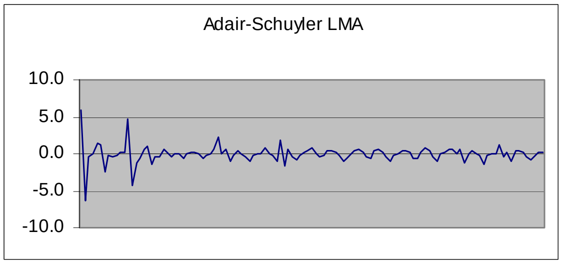


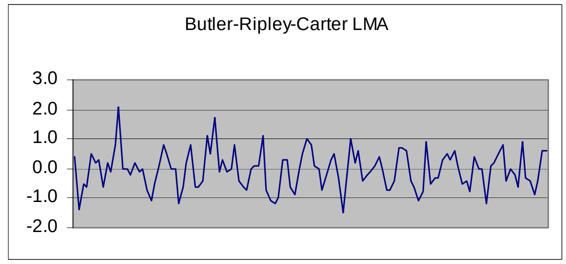


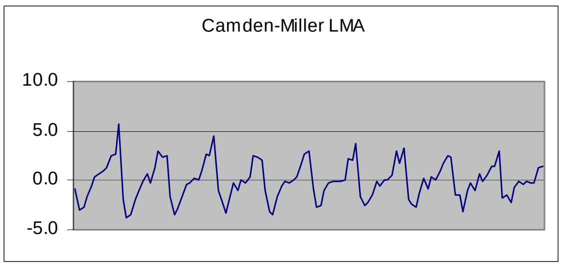


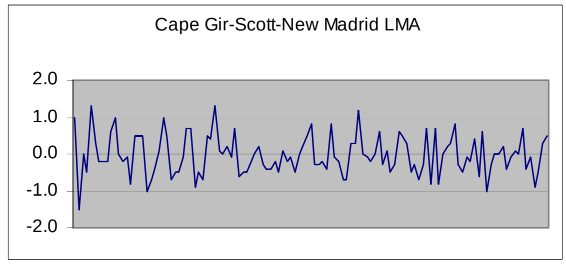


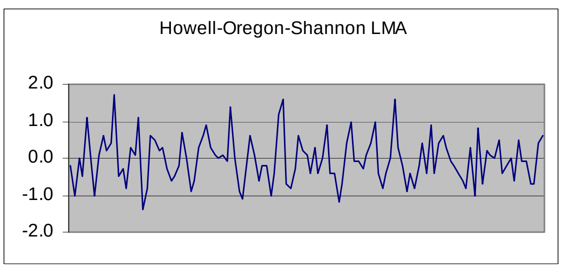


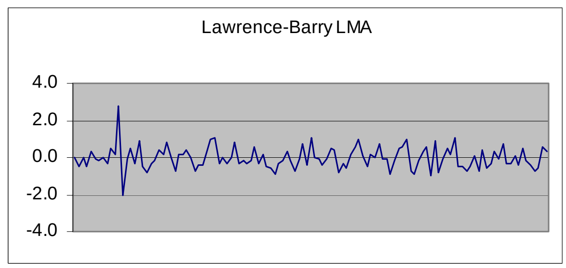

Adair-Schuyler LMA
10.0
5.0
0.0
-5.0
-10.0

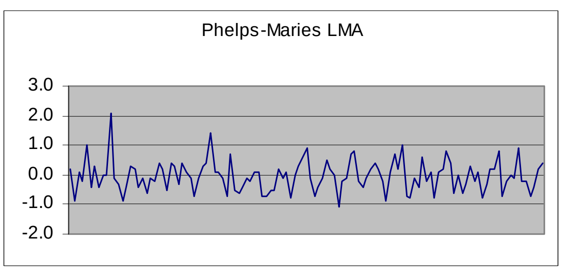

Butler-Ripley-Carter LMA
3.0
2.0
1.0
0.0
-1.0
-2.0

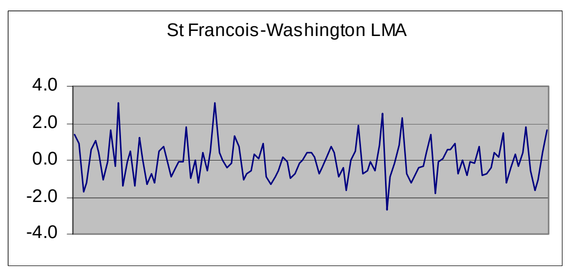

Camden-Miller LMA
10.0
5.0
0.0
-5.0


Cape Gir-Scott-New Madrid LMA
2.0
1.0
0.0
-1.0
-2.0


Howell-Oregon-Shannon LMA
2.0
1.0
0.0
-1.0
-2.0

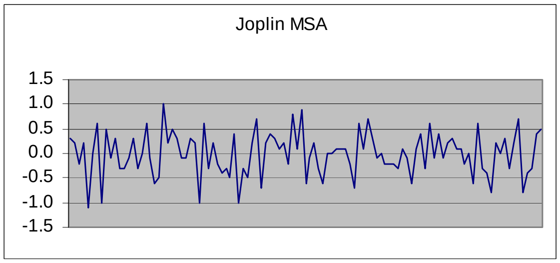

Lawrence-Barry LMA
4.0
2.0
0.0
-2.0
-4.0

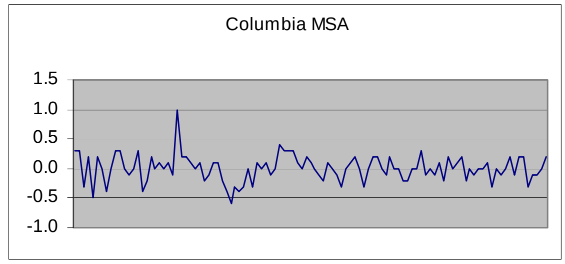

Phelps-Maries LMA
3.0
2.0
1.0
0.0
-1.0
-2.0

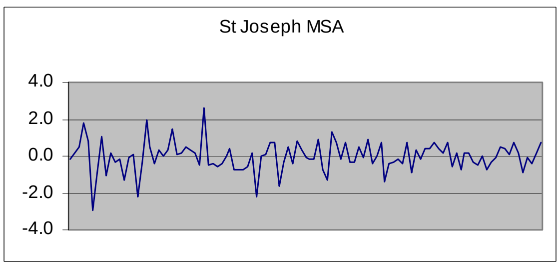

St Francois-Washington LMA
4.0
2.0
0.0
-2.0
-4.0

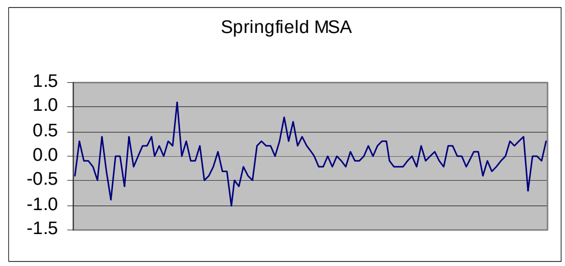
Appendix E

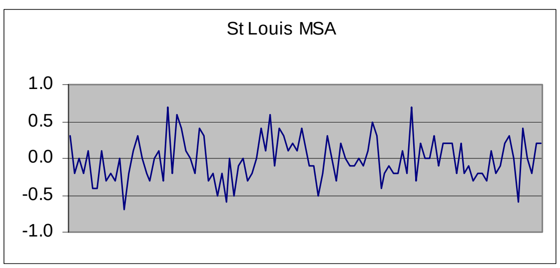
First and Twelfth Difference of Unemployment

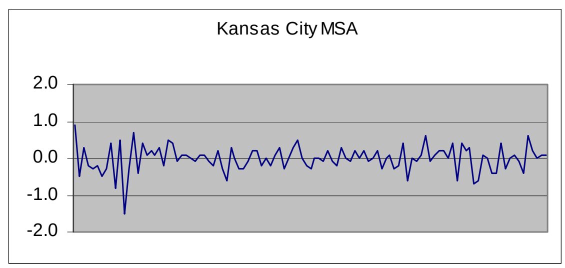


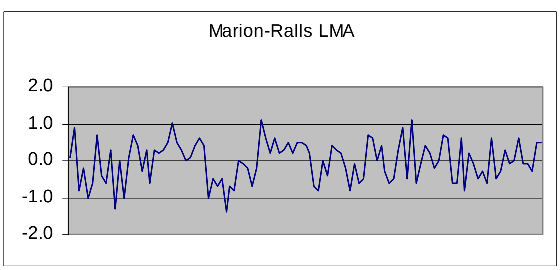


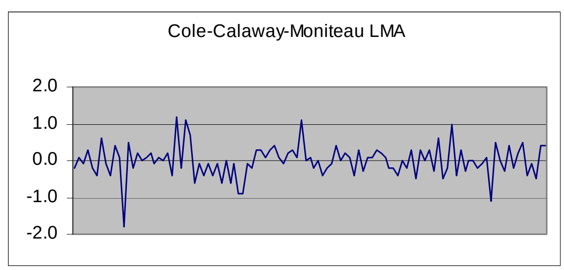


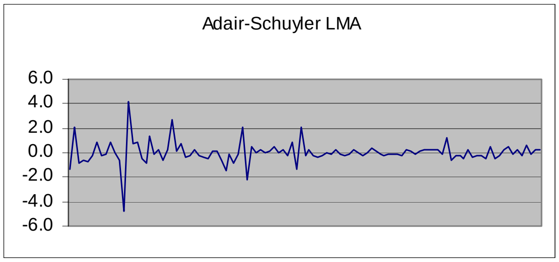


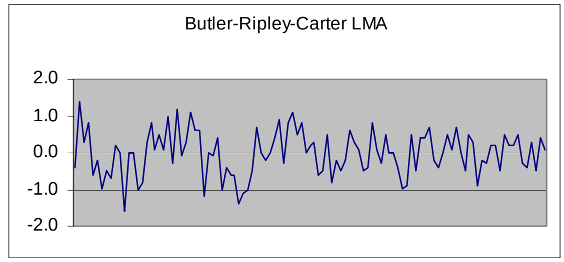


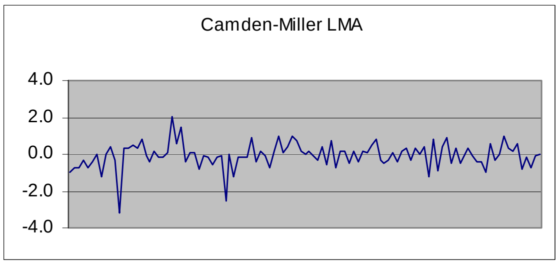


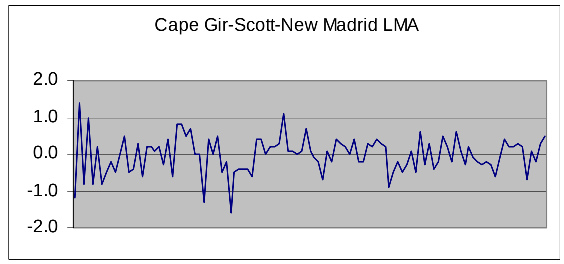


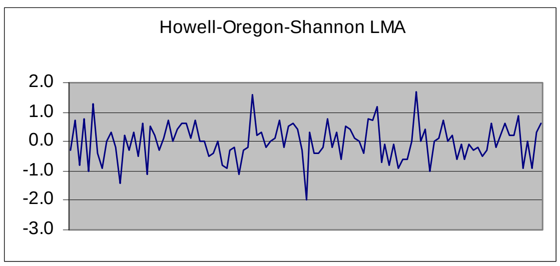


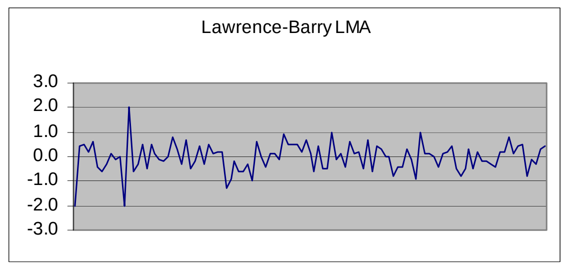

Adair-Schuyler LMA
6.0
4.0
2.0
0.0
-2.0
-4.0
-6.0

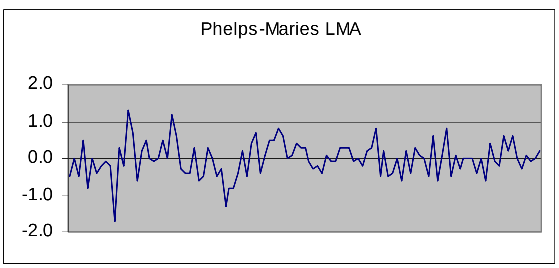

Butler-Ripley-Carter LMA
2.0
1.0
0.0
-1.0
-2.0

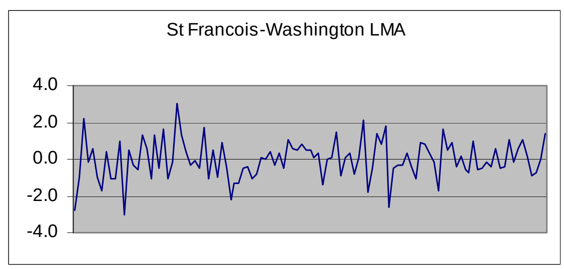

Camden-Miller LMA
4.0
2.0
0.0
-2.0
-4.0


Cape Gir-Scott-New Madrid LMA
2.0
1.0
0.0
-1.0
-2.0


Howell-Oregon-Shannon LMA
2.0
1.0
0.0
-1.0
-2.0
-3.0


Lawrence-Barry LMA
3.0
2.0
1.0
0.0
-1.0
-2.0
-3.0


Phelps-Maries LMA
2.0
1.0
0.0
-1.0
-2.0


St Francois-Washington LMA
4.0
2.0
0.0
-2.0
-4.0

Appendix F

BIC estimates for the autoregressive models

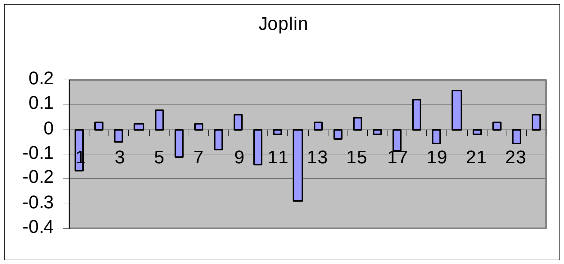
BIC	Joplin	Columbia	St. Joseph	Springfield	St. Louis	Kansas City
AR(1)	471.71671	372.86286	454.66034	264.81751	178.9067	322.17229
AR(2)	466.87305	369.48973	451.33725	266.10709	179.12739	321.55608
AR(3)	463.77829	367.44682	450.62992	266.05691	178.93028	319.91428
AR(4)	462.03875	367.59802	444.74541	267.58712	180.95744	320.33529
AR(5)	456.47203	365.27103	442.88847	266.95233	175.74146	320.54512
AR(6)	456.18145	365.9254	431.33669	267.40898	175.60358	320.8279
AR(7)	456.39933	364.64717	428.31885	265.09812	175.71716	320.71871
AR(8)	456.36939	364.75401	427.93674	266.16365	176.27444	322.26089
AR(9)	456.01229	357.47217	424.77534	264.43516	177.43526	322.41822
AR(10)	453.54131	358.13388	424.79152	263.14647	168.84737	323.57619
AR(11)	449.93049	349.55086	424.40243	261.0123	170.09948	323.14769
AR(12)	445.15186	305.00988	390.24794	202.71391	159.43187	270.83625
AR(13)	390.27562	303.92925	387.73444	201.75844	162.61684	264.45794
AR(14)	368.56178	304.30424	387.75626	202.99594	163.73408	262.30825
AR(15)	353.04595	304.70061	388.51784	203.604	167.03398	261.53503
AR(16)	351.42209	306.15751	381.32692	200.53418	162.32657	260.60381
AR(17)	350.79053	296.97603	381.84761	203.36787	163.00932	258.26207
AR(18)	349.55826	298.35994	380.36172	204.83264	161.9226	260.54667
AR(19)	349.35935	292.15078	380.60605	207.75112	160.68159	262.59806
AR(20)	349.51355	293.77349	377.86579	209.32718	161.74514	264.59825
AR(21)	350.43017	295.02082	377.66747	209.44267	164.56859	266.75813
AR(22)	351.48783	295.93007	374.86279	210.41784	163.91543	255.88701
AR(23)	351.65393	295.49798	375.48572	209.16635	166.87969	256.14778
AR(24)	**329.44567**	**283.48666**	**360.36208**	**195.27313**	**120.09427**	**253.62783**

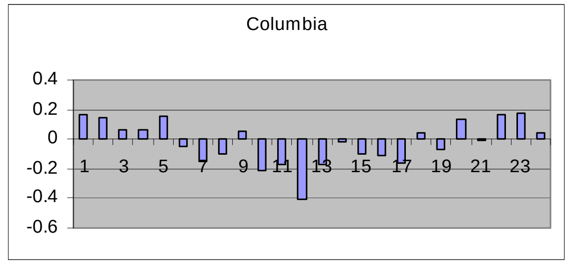
BIC	Marion-Ralls	Cole-Call.-Mont.	Adair-Schuyler	Butler-Ripley	Camden-Miller
AR(1)	419.49074	233.43328	342.18558	506.86509	248.54757
AR(2)	416.02769	231.20894	340.35608	505.05622	242.08725
AR(3)	415.47492	233.1094	340.98202	500.7037	241.75648
AR(4)	415.8789	234.91264	340.39669	500.16523	243.41451
AR(5)	415.65125	237.25518	337.94514	491.60103	244.75474
AR(6)	415.96317	236.32984	339.16907	489.69358	245.41141
AR(7)	415.11685	236.73707	337.96169	483.7631	238.30977
AR(8)	413.21803	237.08462	339.10564	483.03448	238.85094
AR(9)	413.93411	238.82866	340.01835	479.10042	231.61401
AR(10)	413.73828	239.04203	341.13341	476.97077	232.31758
AR(11)	413.82919	239.43382	329.35244	472.53259	232.98617
AR(12)	354.0588	227.21983	306.3326	448.18002	194.30367
AR(13)	352.699	221.73494	302.80325	446.40019	196.78439
AR(14)	350.31157	222.32868	292.83324	441.37498	196.96624
AR(15)	349.79593	224.92899	293.00691	441.00266	199.57078
AR(16)	349.581	225.70962	292.45133	438.08545	202.24677
AR(17)	348.64109	227.33604	292.8458	430.95678	204.50237
AR(18)	348.2902	226.66647	290.77039	428.84379	206.0245
AR(19)	348.67414	218.32272	292.58977	428.81593	208.42077
AR(20)	341.01903	220.783	291.19039	426.76076	210.54259
AR(21)	342.36825	223.46481	291.19766	426.0522	210.59311
AR(22)	342.92839	222.09051	286.98136	421.24981	210.22596
AR(23)	340.79545	219.86437	284.98111	419.61458	208.36037
AR(24)	**338.91631**	**206.03609**	**271.20461**	**395.83252**	**179.06696**

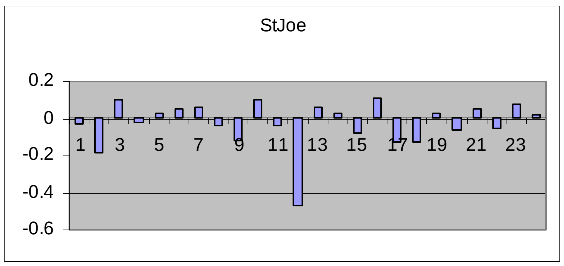
BIC	Cape G.-Scott-N. Mad	Howell-Oregon-Shannon	Lawrence-Barry	Maries-Phelps	St. Fran.-Wash.
AR(1)	323.22071	370.44014	400.55202	391.26879	347.02168
AR(2)	324.49744	371.55294	396.87145	383.24636	327.80739
AR(3)	325.82537	369.45455	392.61815	383.94054	326.39164
AR(4)	327.25184	367.96351	391.59844	383.0918	325.29576
AR(5)	321.69403	367.52154	390.72759	382.12171	324.3529
AR(6)	322.12073	368.56285	387.07886	381.49	324.38254
AR(7)	321.34118	366.9511	387.47606	377.14523	323.5739
AR(8)	317.23141	366.24063	381.62629	378.0273	322.33354
AR(9)	317.6337	366.6421	381.5746	378.42902	321.66095
AR(10)	317.33845	367.71945	379.48873	373.60266	322.03039
AR(11)	318.47826	367.35007	380.0246	373.65858	322.66931
AR(12)	306.44732	341.23472	358.45191	336.49936	300.78973
AR(13)	307.21672	333.61584	359.26189	336.56513	297.52286
AR(14)	307.91917	334.38584	355.84878	334.48603	297.68041
AR(15)	309.27458	335.51554	354.62987	331.91494	297.58696
AR(16)	308.95161	336.1298	354.94059	331.5028	297.44111
AR(17)	309.2673	337.29903	356.17412	329.4824	298.27998
AR(18)	308.92613	338.41322	355.22075	330.35161	299.66098
AR(19)	310.20428	338.63143	355.07065	331.19601	301.0736
AR(20)	305.59578	338.07779	355.97405	328.51265	302.1511
AR(21)	306.11417	338.82984	351.7531	329.22995	301.92986
AR(22)	302.60085	336.85261	352.92212	326.65301	303.2093
AR(23)	297.96129	335.51865	352.4153	327.3166	302.1193
AR(24)	**296.52708**	**329.37714**	**339.67297**	**291.7209**	**274.06365**

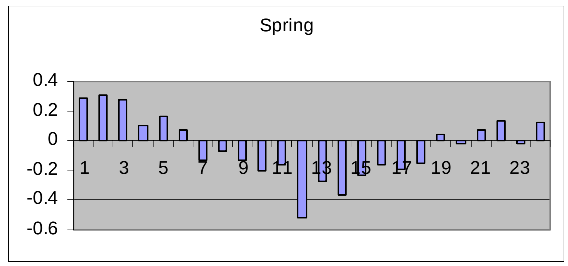
Appendix G

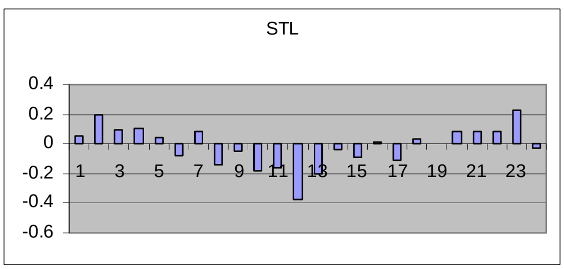
Autocorrelation Functions

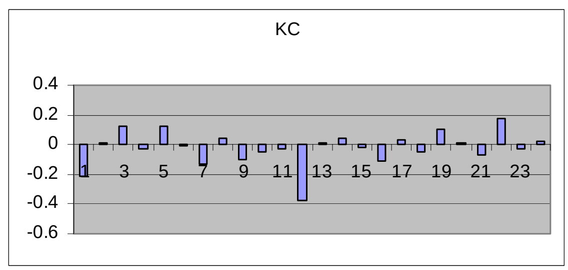


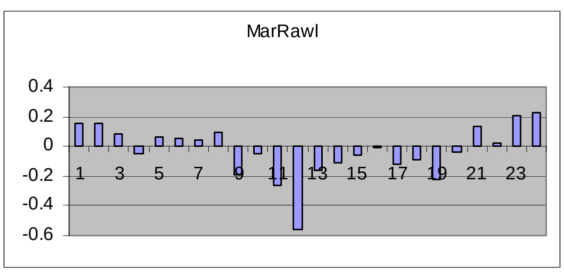


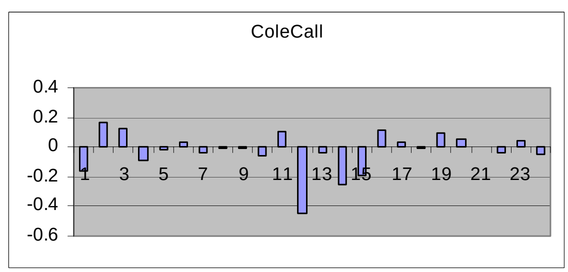


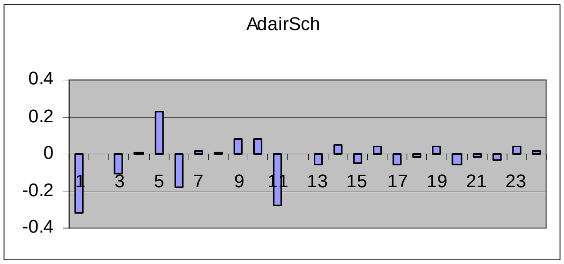








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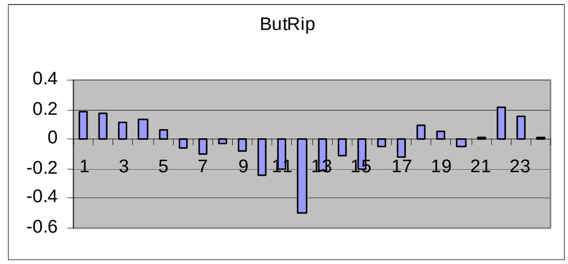
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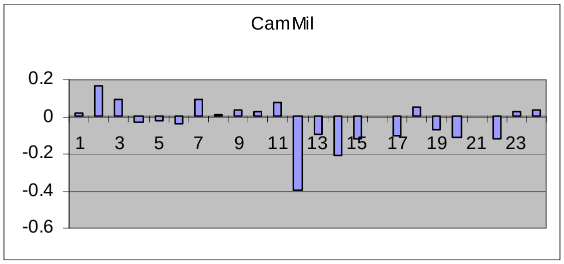
CamMil
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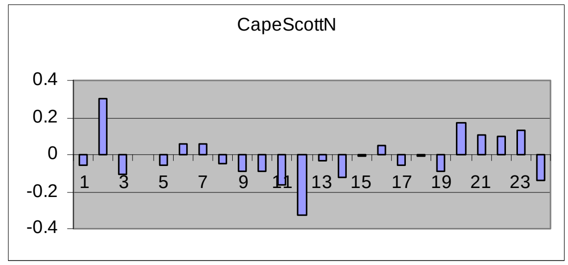
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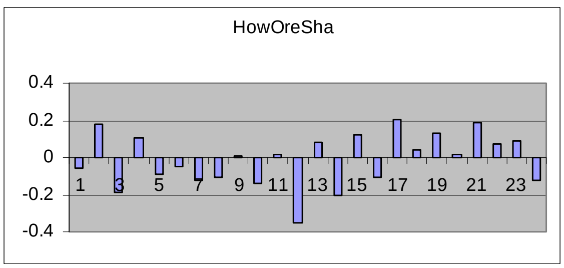
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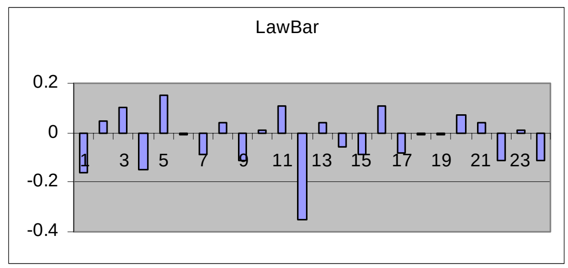
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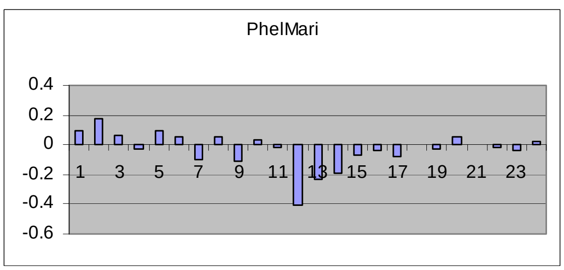
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-0.6
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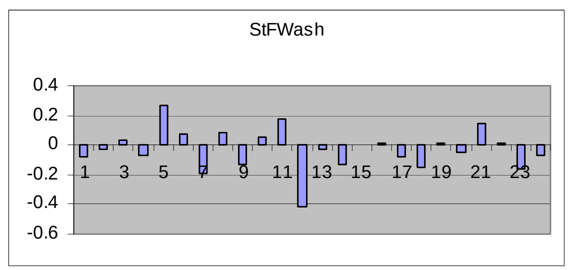
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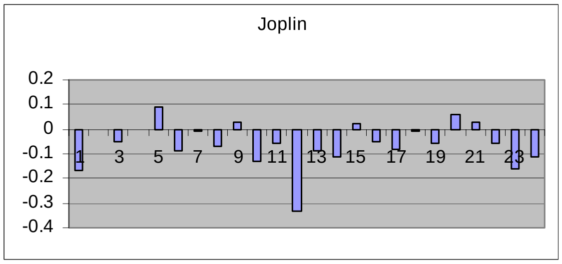
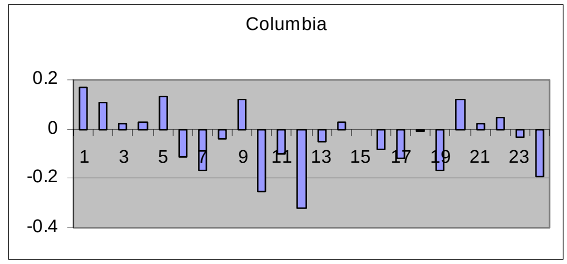
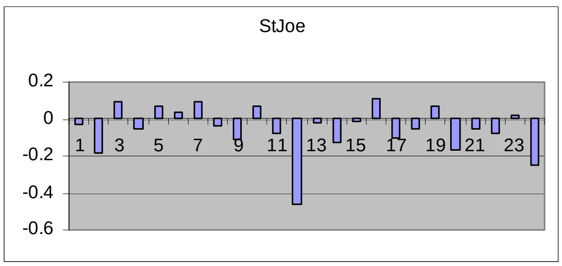
1 3 5 7 9 11 13 15 17 19 21 23

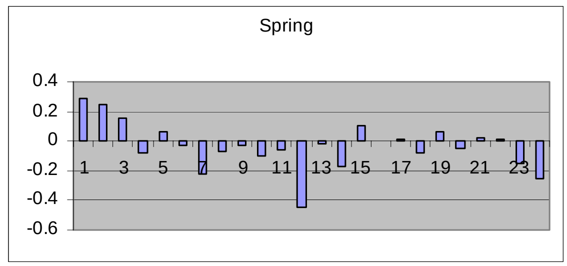
Appendix H

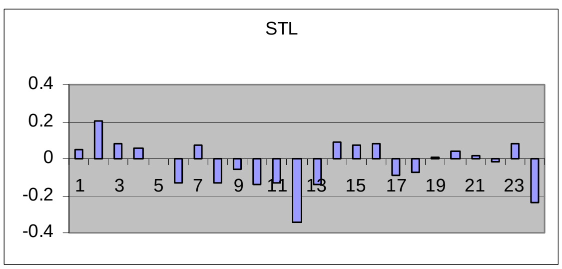
Partial Autocorrelation Functions

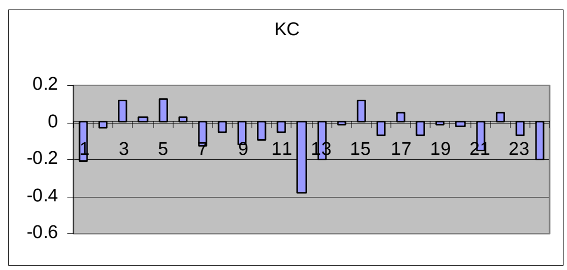


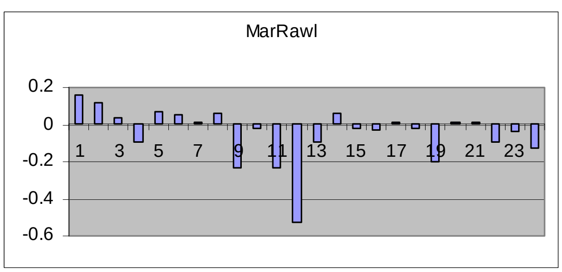


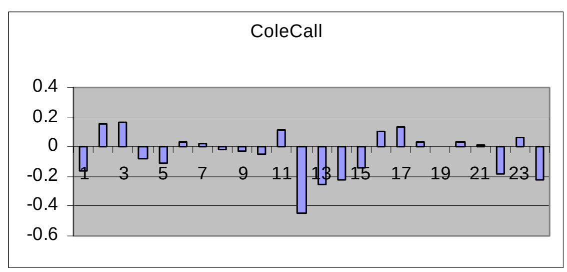


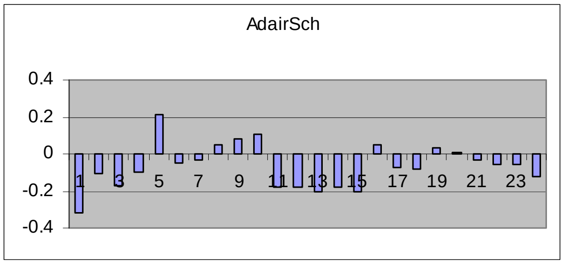








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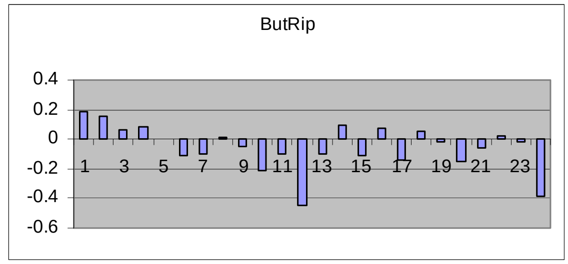
-0.4
1 3 5 7 9 11 13 15 17 19 21 23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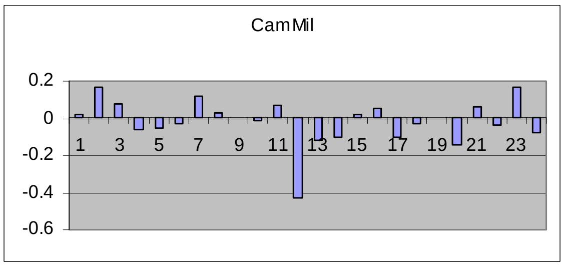
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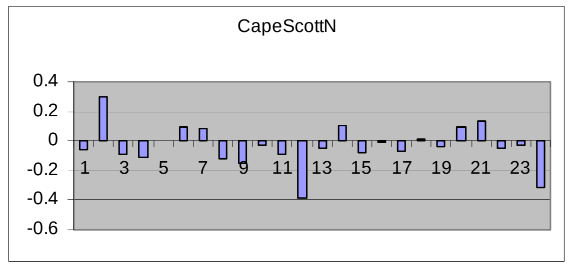
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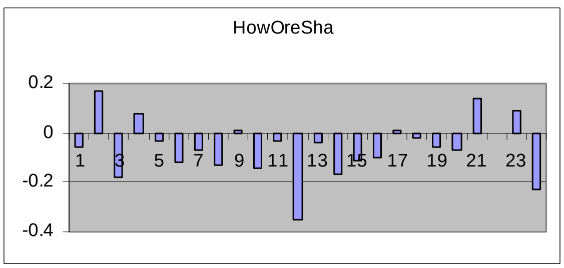
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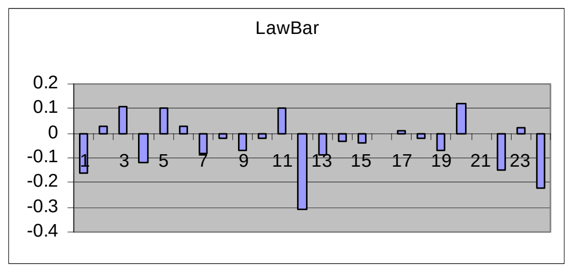
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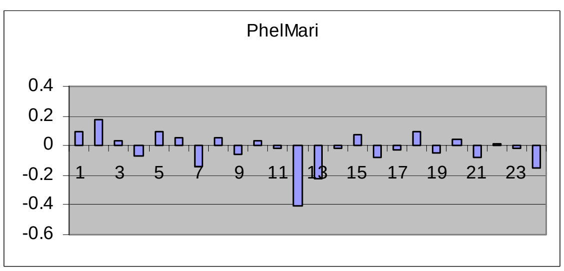
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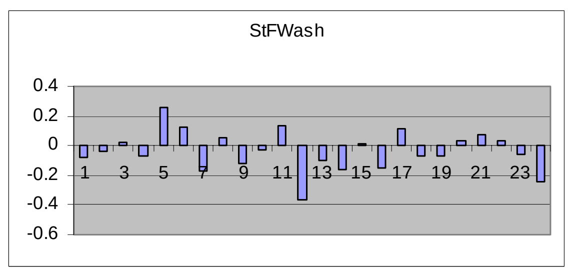
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