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WORKING PAPER NO. 99-7

A BAYESIAN VAR FORECASTING MODEL FOR THE PHILADELPHIA METROPOLITAN AREA

Theodore M. Crone
Federal Reserve Bank of Philadelphia

Michael P. McLaughlin
Federal Reserve Bank of Philadelphia

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A Bayesian VAR Forecasting Model for the Philadelphia Metropolitan Area

Theodore M. Crone
Federal Reserve Bank of Philadelphia

and

Michael P. McLaughlin
Federal Reserve Bank of Philadelphia

The views expressed in this paper are those of the authors and do not necessarily reflect those of the Federal Reserve Bank of Philadelphia, or the Federal Reserve System.

ABSTRACT

Vector-autoregression (VAR) forecast models have been developed for many state economies, including the three states in the Third Federal Reserve District – Pennsylvania, New Jersey, and Delaware. This paper extends that work by developing a Bayesian VAR forecast model for the Philadelphia metropolitan area and the city of Philadelphia.

INTRODUCTION

Forecasts of the national economy have long been a staple of the planning and budgeting process for large corporations and the federal government. But for small firms and state and local governments, a forecast of the regional economy may be more important to their planning process. This demand for regional forecasts challenges the professional forecaster to develop models that produce accurate predictions of the major economic variables for states and metropolitan areas. Several years ago, the Philadelphia Fed developed a small forecasting model for each of the three states in the Third Federal Reserve District—Pennsylvania, New Jersey, and Delaware (Crone, Delaney, Mills, 1992). This paper introduces a similar model that forecasts major economic variables for the Philadelphia metropolitan area and the city of Philadelphia.

The Philadelphia metropolitan area is a natural choice as a region for developing an economic forecast. It is one of the nation's largest metro areas, and it has a diverse economy. Moreover, the area's business cycle is similar, though not identical, to the national cycle. Metropolitan areas in general represent logical geographic divisions for forecasting economic activity because "the general concept adopted for the determination of a standard metropolitan area was that each area should represent an integrated economic unit with a large volume of daily travel and communication between a central city and the outlying parts of the area" (U.S. Bureau of the Census, 1949). The Philadelphia metropolitan area is the fourth largest in the United States and still conforms to the classic description of a metropolitan area—an integrated economy with a densely populated central city to which a large number of workers commute from surrounding suburbs.[1] In 1990, almost a quarter of a million people commuted to the city of Philadelphia to work—about one-third of the wage and salaried workers in the city. The Philadelphia metro area has a population of almost 5 million and supplies more than 2.25 million nonfarm jobs, slightly less than 2 percent of the national totals in both cases. The area has more people and jobs than 30 states, and the city of Philadelphia alone has a larger population and more jobs than 12 states. The Philadelphia metro area contains more than 40 percent of the population in the Third Federal Reserve District and about 50 percent of the jobs.

The Philadelphia economy is not only large but also diverse. We would expect the distribution of jobs in few, if any, metropolitan areas to exactly mirror the distribution in the nation as a whole, but the distribution in Philadelphia comes close. Jobs in the Philadelphia area are somewhat more concentrated in financial and nonfinancial services than in the nation as a whole, and the other major job categories (construction, manufacturing, transportation and utilities, trade, and government) are somewhat underrepresented in the Philadelphia economy.[2] Despite these differences, the distribution of jobs in the Philadelphia area mirrors the national distribution fairly closely when compared to the other nine largest metropolitan areas in the country. (See Appendix A: *Measuring the Relative Importance of Industries Across Metropolitan Areas.)*

[1]The Philadelphia metropolitan area includes five counties in Pennsylvania (Philadelphia, Bucks, Chester, Delaware, and Montgomery) and four counties in New Jersey (Burlington, Camden, Gloucester, and Salem).

[2]The Philadelphia area has about 6.8 percent more of its jobs in nonfinancial services and about 1.1 percent more in financial services than the nation. The area has an especially high concentration of jobs in the insurance industry, legal services, health services, social services, and private education. The underrepresentation in Philadelphia ranges from 0.5 percent for transportation and public utilities to 3.1 percent for government (federal, state, and local).

Even though the structure of the Philadelphia economy has closely resembled the national economy in recent decades, significant shifts have occurred in the last 30 years. Prior to the 1980s, the Philadelphia area had a larger proportion of its jobs in the manufacturing sector than the nation. But Philadelphia has been losing manufacturing jobs at a much faster pace than the nation, so the region's economy is now less manufacturing oriented than the U.S. economy.[3] Crone (1997) outlines some of the reasons for this decline in manufacturing jobs, which has been a major factor in keeping Philadelphia's overall job growth below the U.S. average.[4] Nonfarm job growth in the metro area has averaged less than 1 percent a year since 1967, compared with 2 percent a year for the nation.

Although trend growth in the Philadelphia area has been slower than the national average, the business cycles have been similar. Since the late 1960s, both the nation and the metro area have suffered five periods of sustained job losses (losses lasting two consecutive quarters or more). The national and regional downturns have occurred at approximately the same time, but downturns in the Philadelphia area have tended to begin a bit earlier and last a bit longer. In most cases, the differences in timing have been narrow. At all but two of the 10 turning points, the cyclical high or low employment levels in the metro area were within one quarter of the cyclical highs and lows in the nation (Figure). Job growth in the metro area is also much more volatile than job growth

[3]Since their peak in 1967, manufacturing jobs in the Philadelphia metro area have declined almost 50 percent, while the nation has lost about 4 percent of its manufacturing jobs. Manufacturing jobs in the nation did not peak until 1979.

[4]The loss of manufacturing jobs is not the only factor, however. Nonmanufacturing jobs have been increasing in the area, but not nearly as fast as in the nation. Nonmanufacturing jobs in the Philadelphia area have increased almost 80 percent since 1967, but nationally they have risen more than 130 percent.

in the nation, and there have been isolated quarters in some expansions when the metro area has lost jobs.

The history of job growth in the city of Philadelphia has been somewhat different. For most of the past 30 years, the city has been losing jobs. Nevertheless, the national and metro area patterns are reflected in the city data. When national job growth has been strong, losses in the city have been less severe, and when the nation was losing jobs, losses in the city were even larger. The city's tax structure sets its economy apart as a distinct segment of the metro area's economy. For evidence of how the city's tax structure affects its job growth relative to the nation's see Inman (1992).

THE BASIC BVAR MODEL

The basic model developed to forecast economic variables for the Philadelphia metropolitan area and the city is a Bayesian vector-autoregression (BVAR) model employing a modified version of what has become known as the Minnesota prior (Todd, 1984). The general form of a BVAR model resembles the general form of an unrestricted VAR model.

where:

Y_t = an n x 1 vector of the values of all the variables in the system at time t.

D = an n x 1 vector representing the deterministic component of Yt.

β_j = an n x n matrix of coefficients on the t-j lagged values of Yt, and

$E[g_t g_s'] = \Sigma$, if t = s, and 0 otherwise.

The Bayesian version of the VAR differs from the unrestricted version by incorporating the forecaster's prior beliefs about the most likely values of the $\equiv_j$'s. Prior beliefs are embodied in the estimation procedure by maximizing the likelihood function weighted by the probability density function of the parameters, given the forecaster's priors about the values of the parameters (Doan, Litterman, and Sims, 1984). The distributions of the parameters are assumed to be normal and therefore can be completely defined by means and variances. Thus each parameter is assigned a prior mean and variance. A wider variance about the mean indicates that the researcher has less confidence that the prior mean is the true one.

Rather than assigning each of these means and variances independently, researchers at the University of Minnesota and the Federal Reserve Bank of Minneapolis developed a method of systematically imposing some basic beliefs on the possible values of $\equiv_j$ in equation (1). The key to the systematic assignment of means and variances is the so-called Minnesota prior. Since forecasts based on the random walk hypothesis are often as good as structural forecasts for many economic variables, the Minnesota prior gives considerable weight to the possibility that each variable in the system follows a random walk. In other words, the best estimate of a variable's current value is its value in the previous period. In accordance with the random walk hypothesis, the prior mean of the coefficient on the own first lag of each variable is one. The prior means on all of the other own lags and on all cross lags are zero.

Even though the random walk may perform well relative to structural models, the very effort to estimate a VAR model indicates that the forecaster does not consider it an adequate forecast. Therefore, in a BVAR model the forecaster assigns variances to the prior means based on how confident he is that the prior means are the true ones. The Minnesota prior assigns more confidence to the belief that the coefficients on the cross lags are close to zero, and therefore, the variances imposed on the cross-lag coefficients are smaller than the variance imposed on the coefficient for the variable's own first lag. Finally, the longer the lag on each variable, the more confidence the forecaster has that the lagged variable has no effect on the value of the variable to be forecast. Therefore, coefficients on longer lags are generally assigned smaller variances around the zero mean.

In developing a BVAR model in the Minnesota tradition, the model-builder generally begins with a set of priors that would produce a forecast close to the random walk. The prior variances on each of the parameters are then sequentially adjusted, and the performance of each new specification of the model is compared with the preceding one. Performance is judged by the out-of-sample forecast errors. When the model-builder is satisfied that he has tried a sufficient number of specifications, he chooses the model that produced the smallest average out-of-sample forecast errors. In this way, the original priors are modified in light of the historical data.

The Minnesota system of priors has been made conveniently operational in a RATS software program in which four sets of parameters, called hyperparameters, are chosen to specify the prior beliefs in a BVAR system (Doan, 1992). The first set of hyperparameters is the means of the own first lags on each of the variables in the system. These are set to one, reflecting the prior weight given the random walk hypothesis. The prior means of the other own lags and of all lags on other variables are always zero.

The hyperparameters that specify the variances around the prior means correspond to elements in the following expression:

$$S(i,k,j) = \{(\, g(j)f(i,k)\}\, s_i/s_k$$

where:

S(i,k,j) = the standard deviation of the prior distribution of the coefficient on lag j of variable k in equation i, and

s_i = the standard error of a univariate autoregression on equation i.

The ratio s_i/s_k scales the standard deviations to correct for the different magnitudes of the variables in the system. The three quantities in brackets represent three sets of hyperparameters that determine the relative size of the variances.

f(i,k) = a parameter in the equation for variable i specifying the tightness on variable k relative to variable i. By definition f(i,i) = 1. Since the researcher is generally more confident that own lags are more important in the forecast of a variable than cross lags, the variances on the cross lags around the zero mean are generally tighter than on the own lags. Therefore, $f(i,k) \geq 1$ for $i \uparrow k$. The researcher specifies a matrix of f(i,k).

g(j) = a function that determines the tightness on lag j relative to lag j-1. The larger the parameter designated for the function g(j), the more rapidly the variances decrease as the lag length increases. In a RATS program this parameter is designated by "decay."

(= a parameter that determines the overall tightness of the variances. Because of the restrictions placed on g(j) and f(i,k), (is the standard deviation on the own first lag in each equation. In a RATS program this parameter is designated by "tight."

SELECTING THE VARIABLES IN THE PHILADELPHIA MODEL

We are most interested in a forecast of nonfarm employment and the unemployment rate for the metropolitan area and the city. Nonfarm employment is the most comprehensive, timely measure of economic activity available for the metro area or the city.[5] And economic analysts regularly point to changes in nonfarm employment and the level of the unemployment rate as indicators of the strength or weakness of regional economies, and not without justification. At the national level, changes in these two variables are important factors in determining official business cycles (Moore, 1983). However, peaks and troughs in nonfarm employment and the unemployment rate do not always coincide with the official beginning or end of the national business cycle. At the metropolitan level, there are no official business cycles, and changes in employment and the unemployment rate are the best indicators of the cycle.

[5]We would like to have a broad measure of regional output such as “gross regional product” that would be analogous to gross domestic product—the most comprehensive measure of output for the nation. Unfortunately, we do not have such a measure. Personal income data are available for the metropolitan area, but they are published with a considerable lag and only on an annual basis, so we cannot use them in our quarterly model.

Our forecast model includes two other regional variables—housing permits and initial unemployment claims, both for the metro area.[6] Housing permits and initial unemployment claims follow a cyclical pattern, but they tend to lead the general business cycle at the national level. That is, housing permits tend to decline and initial unemployment claims tend to rise before the onset of a downturn or recession. For this reason, changes in permits and initial unemployment claims are useful in forecasting more comprehensive measures of the economy, such as employment and the unemployment rate.[7] Thus, our Philadelphia model contains six regional variables—four for the metropolitan area and two for the city of Philadelphia (Table 1). These six variables are the ones we are most interested in forecasting.

We supplement these with eight national variables, which are mainly used to help forecast the metro-area and city variables (Table 2). We include all the national counterparts to the regional variables in the model. We also include some national variables, such as real gross domestic product, because they are comprehensive measures of the U.S. economy. Finally, we include some financial variables, such as the difference between the yield on 10-year Treasury bonds and the federal funds rate (the overnight interbank loan rate) because they have been found useful in forecasting the national economy and are valuable in forecasting some of the metro-area and city variables in our model (Bernanke, 1990).

---

[6]Housing permits are also available for the city of Philadelphia, but the numbers are very small and the pattern is erratic, so we did not use the city housing permits in our model.

[7]There is independent interest in forecasts of housing permits because they are the best regional measure of residential construction, and our model produces a forecast of housing permits for the Philadelphia area.

In most regional VARs, the regional economies being forecast are considered too small for past values of regional variables to influence the national economy over and above the influence of the past values of the corresponding national variables. Therefore, the systems are generally block recursive, that is, the national variables are allowed to influence the regional variables but not vice versa. We employ the same principle in our model and extend the block recursive relationship to the metropolitan area and the city. Thus, the metro-area variables are allowed to influence the city variables but not vice versa.

SPECIFICATION AND ESTIMATION OF THE MODEL

The model for the Philadelphia MSA and the city follows the specification in equation (1) with all of the variables in log form except the unemployment rates, the interest rate spread, and the inflation rate. The model is quarterly, with four lags on all the variables in each equation.

To choose among alternative model specifications, we evaluated relative values of the root mean squared errors (RMSE). We examined the statistic for the one-step-ahead through four-step-ahead forecasts to determine the relative performance of various specifications of the model. We began the model selection process with a univariate benchmark model,[13] generating an out-of-sample RMSE for the time period 1989:I through 1998:IV. In evaluating subsequent versions of the model, we compared the RMSE for the four-step-ahead forecasts with the previous version. We adjusted the prior

[13] In practice we included the cross lags in the system for this benchmark case but set the prior variances around the zero mean so tight that the cross lags were allowed to have virtually no effect on the forecast.

variances for the cross lags equation by equation and variable by variable until the adjustments produced little or no improvement in the RMSE. We then adjusted the overall tightness and decay parameters again using the relative RMSE as our criterion for choosing alternative specifications. In every case the final specification improved upon the random walk and the univariate benchmark forecast. The RATS program for the final specification of the model is given in Appendix B.

HISTORICAL PERFORMANCE OF THE MODEL

Unlike forecasts from structural models, VAR forecasts are generally reported without any subjective adjustments. Thus one can recreate the historical errors the forecast would have produced for any given period if the forecast had been in use. Using the final specifications of our model, we calculated one-quarter-ahead through four-quarter-ahead out-of-sample forecast errors for all the regional variables included in our system. The errors for the unemployment rates are expressed as percentage points; all other errors listed in the tables are expressed as percentages (Tables 3 and 4). For each period, the out-of-sample errors were calculated using the model estimated with all the historical data up to the beginning of the out-of-sample period. Two general patterns appear among these forecast errors. First, the errors for any particular variable become larger as the time horizon increases. Second, the errors are larger for the city of Philadelphia then for the metropolitan area.

CONCLUSION

It remains difficult to accurately forecast the economy of metro areas and individual cities, but the development of time-series models has made the process easier and, in many cases, well worth the effort. The size and diversity of the Philadelphia metropolitan area make it a natural candidate for which to develop a forecasting model. For many local businesses, organizations, and governments, a reasonable forecast for the area's economy can be helpful to the planning process. The time-series model we have developed provides an additional tool to the economist in charting the course of the Philadelphia economy. The historical errors in the forecast are a reminder, however, that this tool should not be used alone.

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Appendix A: Measuring the Relative Importance of Industries Across Metropolitan Areas

One measure of a metro area's relative specialization in a given industry is the "location quotient." This quotient is calculated as the proportion of an area's employment (or output) in a given industry divided by the proportion of the nation's employment (or output) in that industry. A location quotient equal to one indicates that the industry in question is neither over- nor underrepresented in the region relative to the nation. Industries with location quotients greater than one have relatively more importance in the region than in the nation. The reverse is true for industries with location quotients less than one. Table 5 presents location quotients for the major industry divisions in the 10 largest metropolitan areas. Since output measures are not available at the metropolitan level, these location quotients are based on nonfarm employment.

Philadelphia's location quotients in 1998 ranged from 0.75 for construction and mining to 1.23 for nonfinancial business and personal services.[*] This means that the proportion of jobs in construction and mining in the Philadelphia metro area is 25 percent less than the proportion nationwide. Similarly, the proportion of jobs in nonfinancial services in Philadelphia is 23 percent higher than the proportion in the United States. Three of the other top 10 metro areas (Los Angeles, New York, and Boston) have a lower percentage of their jobs in construction and mining than does Philadelphia. And New York, Washington, and Boston have a higher percentage of jobs in nonfinancial services than Philadelphia. Every one of the other nine metro areas in the table except Chicago has

[*]Because there are so few jobs in the mining and extractive industries in the Philadelphia area, the Bureau of Labor Statistics combines the employment data for this sector with data for the construction industry.

at least one location quotient that is lower than Philadelphia's lowest, and every one has at least one location quotient that is higher than Philadelphia's highest. For each of the major industry divisions, Philadelphia's location quotient ranks between fourth and seventh among the top 10 metropolitan areas. None of Philadelphia's location quotients are at the extremes among the nation's largest metro areas.

Appendix B: RATS program for the Philadelphia forecast:

```
***********************************************************************************************

  Data naming convention:  AABBCC_XXXX:
       AA = series format
              lg = log
              x  = series containing both historical and forecasted data points
       BB = data series
              nt = total payroll employment
              ur = unemployment rate
              cl = initial unemployment claims
              bp = housing permits
              ip = industrial production
              rt = difference between ten year treasury bond yield and federal funds rate
              in = inflation rate
              gd = GDP
              rs = retail sales
              tn = ten year treasury bond yield
              yp = personal income
       CC = area
              us = nation
              ph = philadelphia msa
              pc = philadelphia city
       XXX = data type or calculation
             hat = forecast series
              eq = equation

***********************************************************************************************
*
*  Part 1a:  Allocate time periods and input time series data. Update the dates in the
*           below compute statements to correspond to the current quarter.  Note, the US
*           data needs at least one additional historical observation for calculation of
*           the inflation rate.
*                     a) us_begdata: beginning date for national data
*                     b) us_enddata: endding date for forecasted national data
*                     b) begdata: beginning date for regional data
*                     c) enddata: ending date or most recent observation
*
***********************************************************************************************

cal 1970 1 4
all 0 2050:1
compute us_begdata = 1970:1
compute us_enddata = 1999:2
compute begdata  = 1975:1
compute enddata  = 1999:2

open data y:\forecast\us\data\us_data.rat
data(format=rats,org=obs) us_begdata us_enddata cpus
data(format=rats,org=obs) us_begdata us_enddata ipus
data(format=rats,org=obs) us_begdata us_enddata ntus
data(format=rats,org=obs) us_begdata us_enddata urus
data(format=rats,org=obs) us_begdata us_enddata ypus
data(format=rats,org=obs) us_begdata us_enddata bpus
data(format=rats,org=obs) us_begdata us_enddata fdus
data(format=rats,org=obs) us_begdata us_enddata tnus
data(format=rats,org=obs) us_begdata us_enddata clus
data(format=rats,org=obs) us_begdata us_enddata gdus
data(format=rats,org=obs) us_begdata us_enddata rsus

open data y:\forecast\msa\data\ph_data.rat
data(format=rats,org=obs,compact=average) begdata enddata ntph
data(format=rats,org=obs,compact=average) begdata enddata urph
data(format=rats,org=obs,compact=average) begdata enddata bpph
data(format=rats,org=obs,compact=average) begdata enddata clph
data(format=rats,org=obs,compact=average) begdata enddata ntpc
data(format=rats,org=obs,compact=average) begdata enddata urpc
```

```
*********************************************************************************************
*
*  Part 1b: Perform data transformations.
*
*********************************************************************************************

set lggdus = log(gdus)
set lgntus = log(ntus)
set lgypus = log(ypus)
set lgipus = log(ipus)
set lgbpus = log(bpus)
set lgclus = log(clus)
set lgcpus = log(cpus)
set lgntph = log(ntph)
set lgbpph = log(bpph)
set lgclph = log(clph)
set lgntpc = log(ntpc)
set   rtus = tnus(t)-fdus(t)
set   inus = lgcpus(t)-lgcpus(t-1)

********************************************************************************************
*
*  Part 2a: Set up system.
*
********************************************************************************************

declare series  lggdus_hat   gdus_hat lgntus_hat   ntus_hat   urus_hat lgipus_hat   ipus_hat $
                lgbpus_hat   bpus_hat lgclus_hat   clus_hat   rtus_hat   inus_hat lgntph_hat $
                  ntph_hat   urph_hat lgbpph_hat   bpph_hat lgclph_hat   clph_hat lgntpc_hat $
                  ntpc_hat   urpc_hat
system gdus_eq1  ntus_eq2  urus_eq3  ipus_eq4  bpus_eq5  clus_eq6  $
       rtus_eq7  inus_eq8  ntph_eq9  urph_eq10 bpph_eq11 clph_eq12 $
       ntpc_eq13 urpc_eq14
variables lggdus lgntus urus lgipus lgbpus lgclus rtus inus  $
          lgntph urph lgbpph lgclph $
          lgntpc urpc
lags 1 to 4
det constant
specify(tight=.15,type=general,decay=0.5,scale)
# 1.000 0.500 0.001 0.001 0.800 0.001 0.800 0.500 0.001 0.001 0.001 0.001 0.001 0.001 $
  0.800 1.000 0.500 0.800 0.001 0.800 0.001 0.800 0.001 0.001 0.001 0.001 0.001 0.001 $
  0.001 0.800 1.000 0.200 0.001 0.800 0.001 0.500 0.001 0.001 0.001 0.001 0.001 0.001 $
  0.001 0.001 0.200 1.000 0.200 0.001 0.800 0.001 0.001 0.001 0.001 0.001 0.001 0.001 $
  0.001 0.001 0.200 0.001 1.000 0.001 0.001 0.200 0.001 0.001 0.001 0.001 0.001 0.001 $
  0.001 0.001 0.001 0.001 0.200 1.000 0.200 0.800 0.001 0.001 0.001 0.001 0.001 0.001 $
  0.001 0.001 0.200 0.001 0.500 0.001 1.000 0.800 0.001 0.001 0.001 0.001 0.001 0.001 $
  0.001 0.200 0.200 0.001 0.001 0.200 0.001 1.000 0.001 0.001 0.001 0.001 0.001 0.001 $
  0.200 0.200 0.500 0.800 0.200 0.200 0.200 0.800 1.000 0.800 0.800 0.800 0.001 0.001 $
  0.001 0.001 0.800 0.001 0.800 0.800 0.001 0.500 0.001 1.000 0.001 0.800 0.001 0.001 $
  0.001 0.001 0.200 0.001 0.800 0.001 0.200 0.001 0.001 0.001 1.000 0.001 0.001 0.001 $
  0.001 0.001 0.001 0.001 0.500 0.001 0.001 0.800 0.001 0.001 0.001 1.000 0.001 0.001 $
  0.800 0.001 0.001 0.001 0.200 0.001 0.001 0.001 0.001 0.800 0.800 0.001 1.000 0.001 $
  0.001 0.001 0.800 0.001 0.500 0.001 0.001 0.500 0.001 0.001 0.800 0.800 0.001 1.000
end(system)
```

```
*************************************************************************************
*
*  Part 2b: Estimate and forecast.
*
*************************************************************************************

estimate(noprint,noftest,outsigma=v) begdata+4 enddata
forecast 14 6 enddata+1
# gdus_eq1  lggdus_hat
# ntus_eq2  lgntus_hat
# urus_eq3    urus_hat
# ipus_eq4  lgipus_hat
# bpus_eq5  lgbpus_hat
# clus_eq6  lgclus_hat
# rtus_eq7    rtus_hat
# inus_eq8    inus_hat
# ntph_eq9  lgntph_hat
# urph_eq10   urph_hat
# bpph_eq11 lgbpph_hat
# clph_eq12 lgclph_hat
# ntpc_eq13 lgntpc_hat
# urpc_eq14   urpc_hat

*************************************************************************************
*
*  Part 3a: Prepare forecasted series and output data.
*
*************************************************************************************

set xntph begdata enddata = exp(lgntph)
set xurph begdata enddata = urph
set xbpph begdata enddata = exp(lgbpph)
set xclph begdata enddata = exp(lgclph)
set xntpc begdata enddata = exp(lgntpc)
set xurpc begdata enddata = urpc
set xntph enddata+1 enddata+6 = exp(lgntph_hat)set xurph enddata+1 enddata+6 = urph_hat
set xbpph enddata+1 enddata+6 = exp(lgbpph_hat)
set xclph enddata+1 enddata+6 = exp(lgclph_hat)
set xntpc enddata+1 enddata+6 = exp(lgntpc_hat)
set xurpc enddata+1 enddata+6 = urpc_hat
```

Table 1
Regional Variables in the Philadelphia Forecast Model

NTPH =	Total Philadelphia MSA nonagricultural employment (SA, thousands)
URPH =	Philadelphia MSA civilian unemployment rate (SA, %)
BPPH =	Philadelphia MSA housing permits (SA)
CLPH =	Philadelphia MSA initial unemployment claims (SA)
NTPC =	Total Philadelphia city nonagricultural employment (SA, thousands)
URPC =	Philadelphia city civilian unemployment rate (SA, %)

Table 2
National Variables in the Philadelphia Forecast Model

GDUS =	Gross domestic product, (SAAR, chained 1992 dollars)
NTUS =	Total U.S. nonagricultural employment (SA, thousands)
URUS =	U.S. civilian unemployment rate (SA, %)
IPUS =	Industrial production (SA, 1992=100)
BPUS =	Total U.S. housing permits (SAAR, thousands)
CLUS =	U.S. initial unemployment insurance claims (SA, thousands)
RTUS =	Spread between the yield on the 10-year Treasuries and the federal funds rate
INUS =	Inflation rate; logged difference of the consumer price index

Table 3
Historical Out-of-Sample Forecast Errors
Root Mean Squared Error 1989:I to 1998:IV
Philadelphia Metropolitan Area

Forecast (Quarters)	*Payroll Employment (Percent)*	*Unemployment Rate (Percentage Points)*	*Building Permits (Percent)*	*Initial Unemployment Claims (Percent)*
1	0.4	0.2	11.7	4.8
2	0.6	0.4	14.5	7.6
3	0.9	0.5	15.6	9.3
4	1.2	0.6	16.3	10.9

Table 4
Historical Out-of-Sample Forecast Errors
Root Mean Squared Error 1989:I to 1998:IV
Philadelphia City

Forecast (Quarters)	*Payroll Employment (Percent)*	*Unemployment Rate (Percentage Points)*
1	0.5	0.3
2	0.7	0.5
3	1.0	0.6
4	1.3	0.7

Table 5

Location Quotients for Major Industries in the 10 Largest Metropolitan Areas

Metro Area	*Construction and Mining*	*Manufac-turing*	*Transpor-tation and Public Utilities*	*Trade*	*Finance, Insurance and Real Estate*	*Non-financial Services*	*Govern-ment*
Los Angeles	0.59	1.14	1.09	0.95	0.98	1.10	0.87
New York	0.61	0.52	1.11	0.75	2.19	1.25	1.00
Chicago	0.77	1.07	1.19	0.96	1.31	1.07	0.76
Philadelphia	0.75	0.89	0.91	0.94	1.2	1.23	0.8
Washington	1.00	0.27	0.89	0.8	0.94	1.32	1.45
Detroit	0.77	1.39	0.87	1.01	0.92	1.04	0.70
San Francisco\ Oakland	0.90	0.68	1.38	0.93	1.41	1.12	0.93
Houston	2.00	0.74	1.36	0.97	0.91	1.03	0.82
Atlanta	0.98	0.73	1.64	1.14	1.14	1.00	0.80
Boston	0.61	0.77	0.83	0.92	1.43	1.32	0.75