

Chapter 6

Forecasting With WinSolve

This chapter looks at how WinSolve can be used to produce a model forecast. Forecasting with a model is quite a different exercise from model simulation and the first section examines some of the issues involved. Then, in the second part of the chapter, these issues are illustrated in a tutorial using a very simple model, Klein's Model 1.

6.1 Issues in Forecasting

6.1.1 The ragged edge

Data series are not all released at the same time. This means that, at the time that a forecast has to be produced, the latest observations will often not yet be available for some series. For any period for which a complete set of data is not available, the gaps will need to be filled by forecasting the missing variables, using the model equations. However, where observations are available, then the forecaster will want to use the latest data in preference to the model equation. Thus the period that denotes the edge between where the data ends and the forecast starts will be different for different variables. This is the so-called forecast '*ragged edge*' and it may well change, over the forecast round, as new data is released.

In *WinSolve*, the ragged edge is handled automatically when the data set is incomplete. In this case, the program recognises that the user is forecasting rather than simulating and will automatically impose the ragged edge so that, where data observations exist, these will be used in preference to the relevant model equation.

6.1.2 Projecting exogenous variables

Most models include some exogenous variables that are not explained within the model. In a forecast, some assumption needs to be made about how these variables will behave over the forecast period. In the case of many variables, projection of a simple growth rate may be enough. In other cases, it may be more appropriate to estimate a time series model over the past and use this to project the variable forward over the forecast period. Both these methods are available in *WinSolve* and are illustrated in the tutorial in Section 2.

6.1.3 Using intercept adjustments

The forecaster will often want to make some changes to the ‘pure’ model forecasts. This is generally accomplished by adding intercept adjustments to one or more of the model equations. There are many reasons why intercept adjustments may be needed. They may be a way of incorporating information that is not yet reflected in the data. Alternatively, they can be used to patch up model equations that have been performing badly. Clements and Hendry (1998) and (1999) discuss the use of intercept adjustments and show that they can improve forecasts in a world of non-constant parameters or structural breaks. *WinSolve* has flexible facilities for setting adjustments which may either be additive or multiplicative.

6.2 A Forecasting Tutorial

In this tutorial we make use of Klein’s Model 1. Although this is a very simple model, with only six endogenous variables: *consumption*, *investment*, *priv_wage_bill*, *production*, *profits* and *capital_stock*, and three exogenous variables: *gov_wage_bill*, *gov_expenditure* and *taxes*, it is adequate to illustrate the general principles that are applicable in any model. The model equations are listed below.

We will assume that we are producing a forecast in the year 1929, of the period 1929–1941, using data available in 1929. In constructing the model and data for this exercise, we abstract from two issues. Firstly, we continue to use the model parameter estimates reported in Theil (1971) even though these were obtained using the full data period 1921–1941. Secondly, we use a truncated data set from the data set used for estimation. This ignores any data revisions that may have taken place after 1929. While ignoring these issues means that we are likely to be underestimating the forecast errors associated with the model, this does not matter for our purposes since we are not interested in an *ex post* analysis.

6.2.1 Opening the model


Click on the open a model icon  or select the *Open model* option from the *File* menu. A dialog box opens to allow you to select a model. Select the file *klein1.txt* and click *OK*. A new window will appear on the desktop representing the model object (Figure 6.1). The icon in this window is a



Figure 6.1: The Klein Model Object

link to the model equations. Double clicking this icon opens an editor to view these equations. The notation should be fairly self-explanatory. The *WinSolve* function **time**(1932) is a time trend taking the value one in 1932.

{ Klein's Model I (1920-1941)

Source: Theil (1971) data: p.456; parameter estimates: p.517 }

@ Behavioural equations

$$\text{consumption} = 16.44 + 0.1249*\text{profits} + 0.1631*\text{profits}(-1) \\ + 0.7901*(\text{priv_wage_bill} + \text{gov_wage_bill});$$

$$\text{investment} = 28.18 - 0.0131*\text{profits} + 0.7557*\text{profits}(-1) \\ - 0.1948*\text{capital_stock}(-1);$$

$$\text{priv_wage_bill} = 1.8 + 0.4005*\text{production} \\ + 0.1813*\text{production}(-1) + 0.1497*\mathbf{time}(1932);$$

@ Identities

$$\text{production} = \text{consumption} + \text{investment} + \text{gov_expenditure};$$

$$\text{profits} = \text{production} - \text{priv_wage_bill} - \text{taxes};$$

$$\text{capital_stock} = \text{capital_stock}(-1) + \text{investment};$$

Before a forecast can be made we need to add a data set. This will define the maximum forecast period for the model and provide observations on all exogenous variables, plus initial values for lagged endogenous variables. In

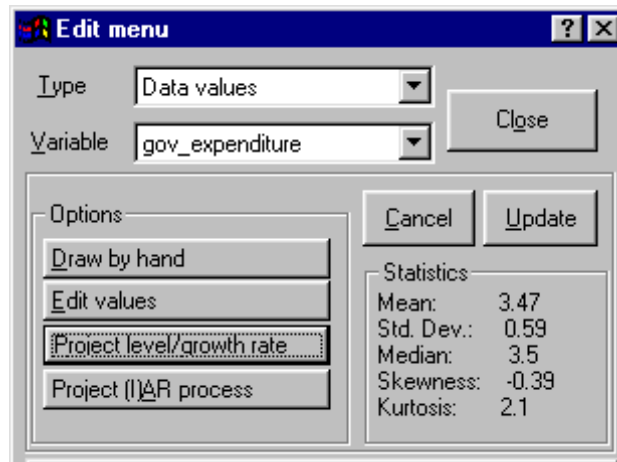




Figure 6.2: Edit dialog box

this case, we have a data set in Lotus spreadsheet format, *kleinf.wk1*, that contains data on all model variables over the period 1919–1928 plus data on some variables for 1929. This represents the ragged edge of data available at the time of the forecast. Click on the (green) open a data file icon  or select the *Open data file* option from the *Data* menu. A dialog box opens to allow a data file to be selected. Select the file *kleinf.wk1* and click *OK*. Notice that several new icons on the toolbar are now ungreyed which indicates that they have become operational. This includes the (yellow) Solve model icon  that allows us to solve the model.

6.2.2 Projecting the exogenous variables

Before we can do a forecast over the forecast horizon 1929–1941, we first need to provide data values for the three exogenous variables: *gov_wage_bill*, *gov_expenditure* and *taxes* over the ‘future’. There are two ways that we might do this. We could choose to impose a path for the exogenous variables, *a priori*, such as a constant growth rate or flat path. Alternatively, we could use an empirical approach and estimate a time series process over the past and project this over the future. Both these methods will be illustrated using the *Edit data/adjustments* option from the *Data* menu. For *gov_expenditure* and *taxes* we will assume a constant growth rate of 3%. For *gov_wage_bill*, we will project a simple time series model.

Open the edit dialog box by clicking on the icon  or by selecting the *Edit data/adjustments* option from the *Data* menu (Figure 6.2). Select type

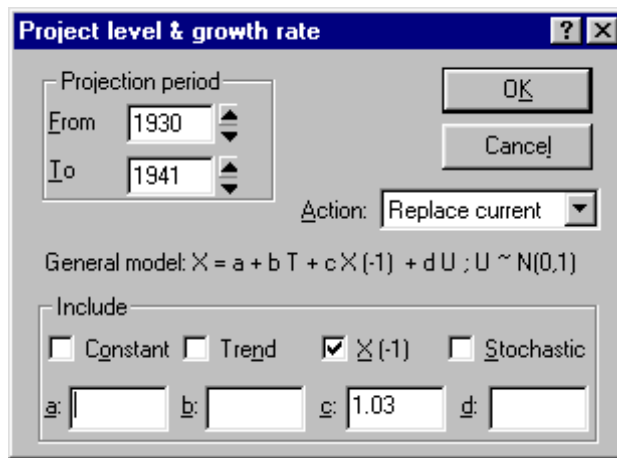


Figure 6.3: Projection dialog box

Data and variable *gov-expenditure*. Then click on the *Project level/growth rate* button. This opens the dialog box in Figure 6.3. The projection period 1930–1941 should already be selected. Click the $X(-1)$ button and put the value 1.03 in the c : box. Then click *OK* to return to the edit dialog and click the *Update* button to update the data. This imposes a 3% growth rate on *gov-expenditure* over the forecast horizon. Then select the variable *taxes* and do the same thing for this variable to set a 3% growth rate over the period 1930–1941.

Finally, select the variable *gov_wage_bill*. For this variable we want to estimate a simple time series model and use this to project the variable forwards. This time, click on the *Project (I)AR process* button. This opens the dialog box in Figure 6.4. This allows us to estimate an (integrated) autoregressive model, either in levels or in logarithms, with optional constant, time trend and seasonal dummies. There is also an option to test the order of integration of the data using augmented Dickey-Fuller tests. The estimated model will then be projected forwards over the forecast horizon. In this case, with only ten observations for estimation, it is unwise to choose too elaborate a model, and there are too few degrees of freedom to put any reliance on the Dickey-Fuller statistics. Instead we choose to estimate a very simple deterministic trend model of the form:

$$\log(y_t) = \alpha + \beta T_t + \varepsilon_t.$$

Select the *Model in logs* button, check the *constant* and *trend* boxes and set *AR lag length* to zero as in Figure 6.4. Then click *OK* to return to the edit

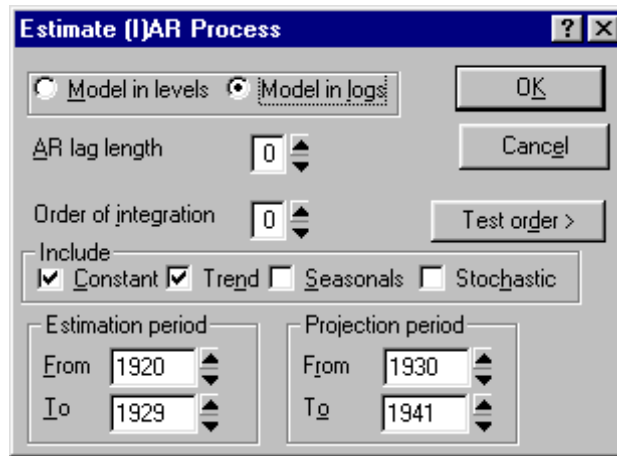




Figure 6.4: (I)AR process dialog box

dialog and click the *Update* button to update the data. Finally click *Close* to leave the dialog box.

6.2.3 A first forecast

We are now in a position to do our first forecast. Because we have an incomplete data set, *WinSolve* will recognise that we are forecasting and will automatically impose the ragged edge.

Click on the Solve model icon  or select the *Solve model* option from the *Solve* menu. This opens the Solution dialog box (Figure ??) which allows various solution options to be selected. Notice that the box *Data has precedence over equations* is checked which shows that *WinSolve* has recognised that the data set is incomplete and so will automatically impose the ragged edge. Select the maximum solution period which is 1921–1941. In fact it is not necessary to start the forecast before 1929 but if we do solve the model over the full period, the earlier years 1921–1928 will give information about how well the model has been performing in the recent past. This will enable us to improve on this initial forecast by suggesting where intercept adjustments might be added. This is explored in the next section. Choose *Dynamic model solution* from the Solution mode list box and click *OK*. This opens the Solution status box (Figure 6.6) which displays information as the model solves. When model solution is complete, the status box can be closed by clicking on the *OK* button.

The forecast results can now be viewed in the *Results* menu. Click on the graph icon  or select the *New table/graph* option in the *Results* menu.

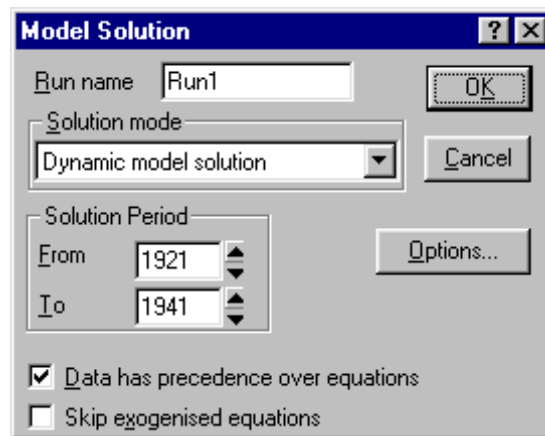


Figure 6.5: Solution dialog box

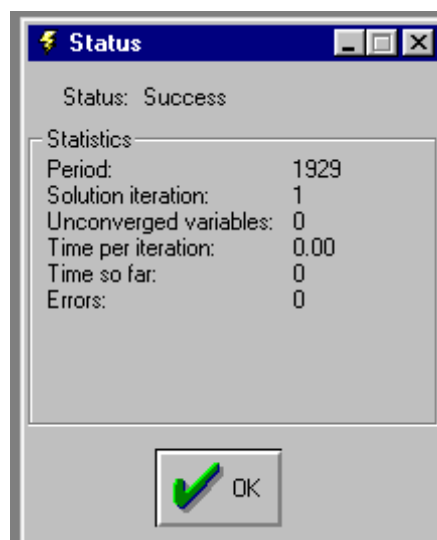


Figure 6.6: Solution status box

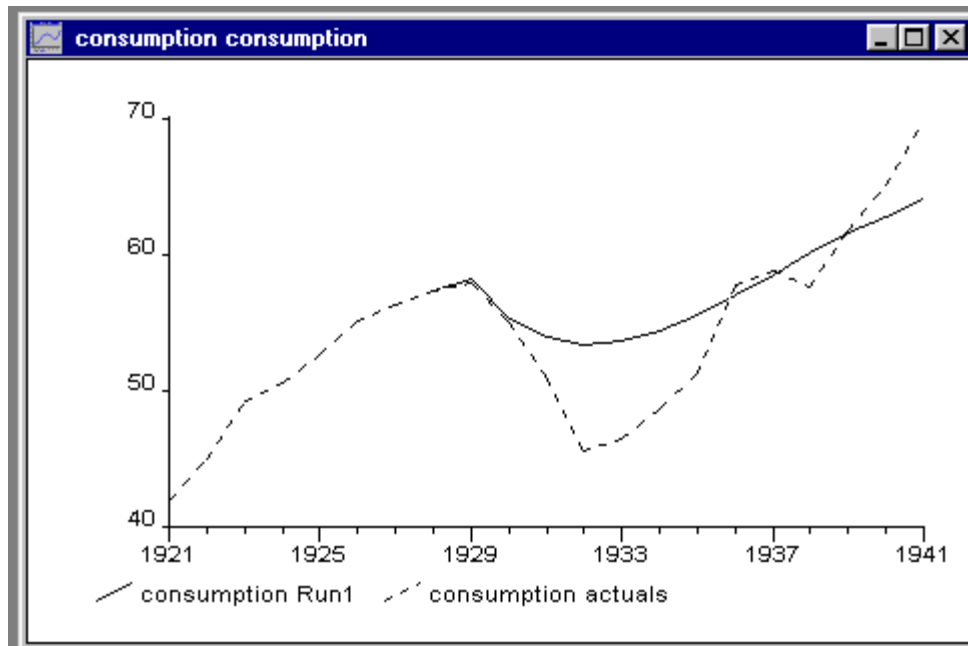



Figure 6.7: Consumption: forecast 1929–1941 plotted against actual outturns

Choose the variable *consumption* and the variable type *Simulation values*. Click the *Add* button to add this item to the graph and then click *OK* to finish. The forecast values will be graphed as in (Figure 6.7). Figure 6.7 also shows actual consumption over the forecast period. This is for reference only since this information would obviously not be available to a genuine forecaster. However, it does show that the model does successfully forecast the Great Depression although it considerably underestimates its true extent.

6.2.4 Improving the forecast: using implicit residuals

Can we improve on this forecast? One piece of information we have available is the performance of the model over the historical period 1921–1928. Even though the model equations are not being used over this period (because of the ragged edge), *WinSolve* does calculate the difference between the actual data values and what the model would have forecast, had it been used. These differences are known as *implicit residuals*. A consistent pattern in the implicit residuals of a variable is evidence of a problem with the prediction of its equation.

Implicit residuals can be viewed in the *Results* menu. Click on the graph icon  or select the *New table/graph* option in the *Results* menu. Select the

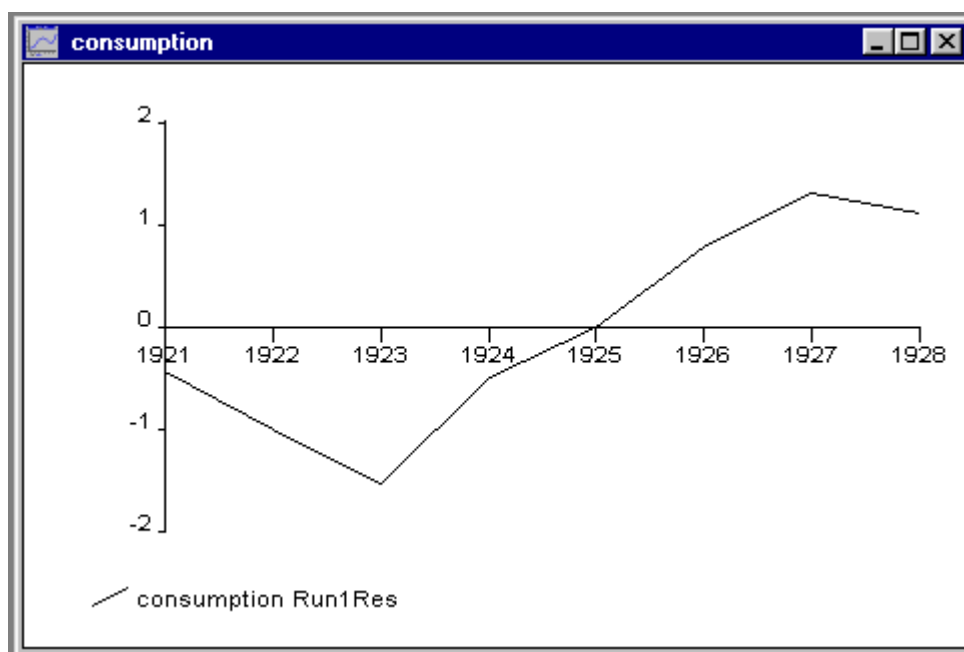


Figure 6.8: Consumption: implicit residuals 1921–1928

variable *consumption* and the variable type *Implicit residuals*. Set the period to 1921–1928 and click the *Add* button and then *OK* to finish. The implicit residuals for consumption will be graphed as in (Figure 6.8). Summary statistics on these residuals can be examined by clicking on the system menu icon in the top right hand corner of the graph and selecting the *View Summary Statistics* option. Note that the mean is $-.04$ which is close to zero and the maximum and minimum values are 1.3 and -1.5 respectively, which are small in comparison with the scale of the variable. However, from the graph we see that there is some evidence of autocorrelation in the residuals with four negative residuals followed by three positive residuals. Considering the most recent three observations, we note that the equation is under-predicting consumption and might wish to compensate for this tendency by projecting an intercept adjustment to the equation over the forecast period.

In order to project model adjustments, it is useful to be able to use the implicit residuals over the past as a guide. *WinSolve* has a facility for setting model adjustments to the implicit residuals from a run. This can be done either for a subset of variables or for all model variables. In this case we will pick up the implicit residuals solely for *consumption*. Select the *Reset data/adjustments* option on the *Data* menu. Select the variable *consumption* and click the button *Set from run*. The dialog box should now look like

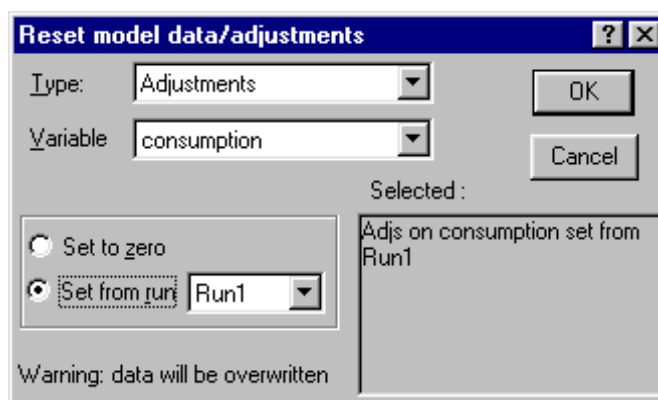





Figure 6.9: Reset data/adjustments dialog box

Figure 6.9. Click the *OK* button to exit.

The implicit residuals for *consumption* can now be used as a basis to project adjustments over the forecast period. We will use the *Project (I)AR Process* option in the *Edit data/adjustments* dialog box to estimate the mean implicit residual over the three observations 1926–1928 and project this over the period 1929–1941. Open the edit dialog box by clicking on the icon  or by selecting the *Edit data/adjustments* option from the *Data* menu. Select type *Adjustments* and variable *consumption* and click on the *Project (I)AR Process* option. In this new dialog box, select the *Model in levels* button, check the *constant* box and set *AR lag length* to zero. Set the estimation period to 1926–1928 and the projection period to 1929–1941 as in Figure 6.10. Then click *OK*. This projects the mean value of 1.0592 over the forecast period. Click the *Update* button to confirm the changes and click *Close* to leave the dialog box. Note that although we have set adjustments over the whole period 1921–1941, those before 1929 will not be used in the forecast because the equation for *consumption* will be overridden by the data values.

We can now run a second forecast using the intercept adjustments to the *consumption* equation that we have estimated. Click on the Solve model icon  or select the *Solve model* option from the *Solve* menu. Choose *Dynamic model solution* from the Solution mode list box and click *OK* to commence solution. When the model has solved, close the status box and open the *New table/graph* dialog box by clicking on the graph icon  or selecting the option on the *Results* menu. We will compare the two consumption forecasts. Select the variable *consumption* from latest run *Run2* and the variable type *Simulation values*. Click the *Add* button. Then change the run to *Run1* and click *Add* again. Then click *OK* to finish. The forecast values from the two

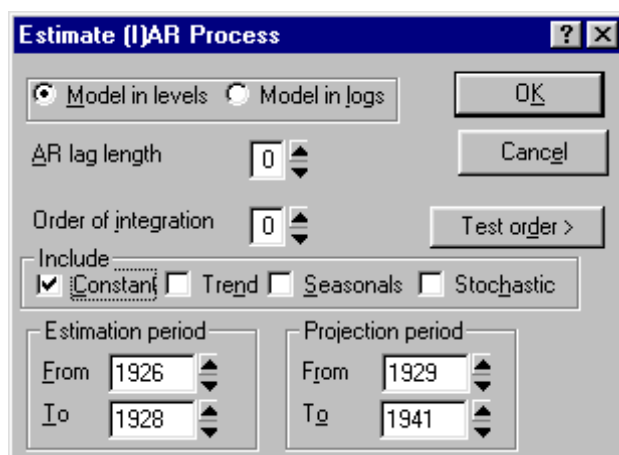


Figure 6.10: Projecting adjustments using (I)AR process dialog box

runs will be graphed as in (Figure 6.11).

As might have been anticipated, the positive intercept correction to consumption leads to a much higher forecast with the predicted depression considerably shallower. In retrospect, it can be seen that, in this particular example, the intercept correction actually gives a worse forecast. This can be attributed to the artificial nature of the illustration. The consumption equation we are using was in fact estimated over the full period 1921–1941 over which its residuals must, by construction, average zero. Adding an intercept adjustment is clearly unnecessary in this case and actually leads to an equation with *biased* single equation residuals. This explains the failure of the correction in this particular example and should not detract from the usefulness of intercept adjustments in general in genuine *a priori* forecasting.

6.3 Further reading

Whitley (1994) is a simple introduction to macroeconomic forecasting. Clements and Hendry (1998) and (1999) are theoretical treatments of forecasting that, among other things, provide a justification for the use of intercept adjustment corrections to forecasts. Pierse (1997) is a concise review of solution methods for nonlinear models, or see Pauletto (1997) for a very detailed treatment.

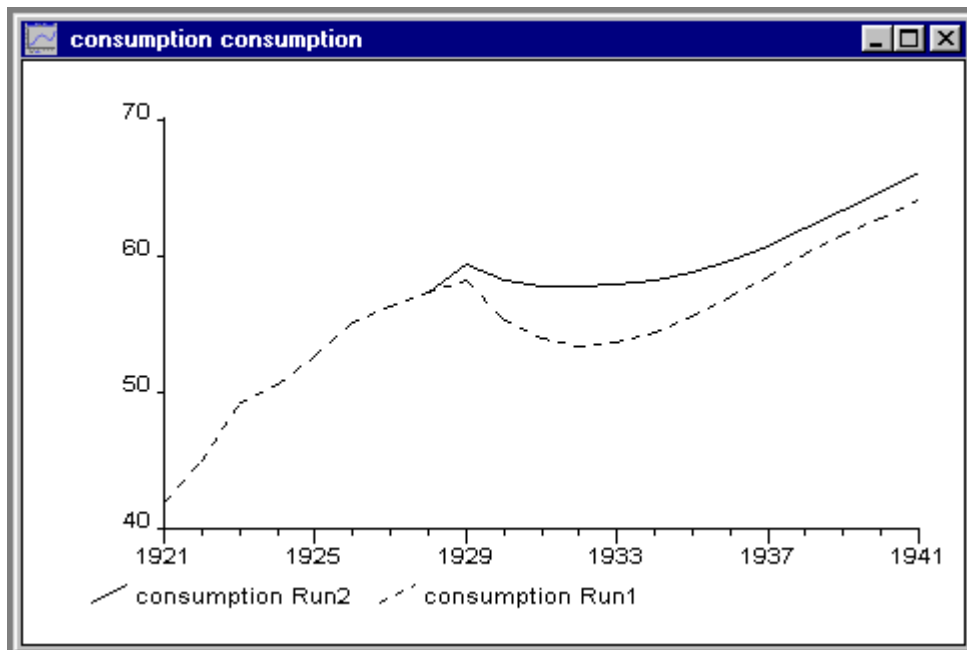


Figure 6.11: Consumption: forecast 1929–1941 from Run1 and Run2

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