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## Constructing a Structural Macroeconomic Model Using Multiple Techniques

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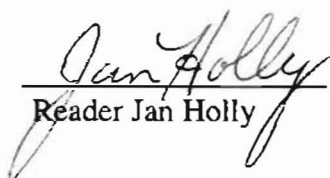
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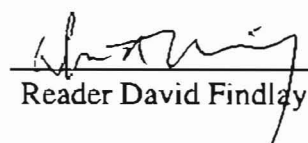
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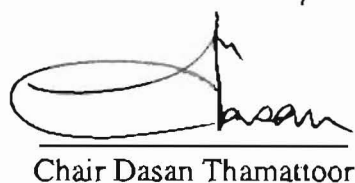
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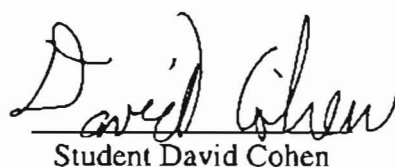
I certify that David Cohen has adequately completed his yearlong senior scholars endeavor.

  
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# Constructing A Structural Macroeconomic Model Using Multiple Techniques

Senior Scholars Program  
Colby College 2004

**BY DAVID COHEN**

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**Abstract-** This project constructs a structural model of the United States Economy. This task is tackled in two separate ways: first using econometric methods and then using a neural network, both with a structure that mimics the structure of the U.S. economy. The structural model tracks the performance of U.S. GDP rather well in a dynamic simulation, with an average error of just over 1 percent. The neural network performed well, but suffered from some theoretical, as well as some implementation issues.

## **1 Introduction**

There are several methods for constructing and estimating models in the econometrician's toolbox. The most prevalent method is standard regression analysis. In particular, linear regression analysis is used for most everything in modeling, since the coefficients have relatively intuitive meaning, and the model as a whole is very understandable to the user.

The fact that a model is understandable is important to several types of people. For instance, being able to see what portion of income will be spent could be extremely helpful to policy makers trying to determine the size of a stimulus package. Academics are another group of people who justify the use of linear regression analysis because of the relative ease of understanding of the coefficients.

In forecasting, however, there are several methods that are far from being theoretical, but that can produce good predictions. These techniques can range from the simple, like univariate trend lines, to more sophisticated vector autoregressive models. These types of models look for patterns in the data, and use them to predict the data series into the future. In the past, neural networks have been used as a more advanced method of non-theoretical forecasting, similar to a nonlinear ARIMA model (Zhang et al., 1997). The

reason that neural networks are generally used as atheoretic models is because of the fact that the weights in the model generally have no intuitive meaning.

The goal of this project is to compare structural models, constructed using different techniques. The first, an econometric model, is constructed using a standard methodology. Following its completion, a model based on neural networks, is constructed to possess the same properties and structure of the econometric model. Following their construction, the two seemingly different models are compared, and shown to be quite similar.

Over the course of this paper, the properties of both theoretical linear regression models, and theoretical neural networks will be looked at. The models will then be built and analyzed.

## **1.1 What is a Structural Macroeconomic Model**

Structural macroeconomic models are built using theoretical economic relationships as the underpinnings for the model. These models rely on systems of simultaneous equations with each equation specifying a single relationship. These models generally attempt to measure the economy as a whole, or one particular section of the economy.

### ***1.1.1 What is the History of the National Product Accounts***

Between World War I and World War II governments began to keep national income and product accounts statistics. The United States commerce department started this practice shortly following the beginning of the Great Depression. The acceptance of John Maynard Keynes's "The General Theory of Employment, Interest, and Money" fueled the development of the product accounts. His seminal work stressed the importance of macroeconomic relationships such as the importance of investment in national product.

The purpose of the National Product Accounts was to be able to analyze current economic conditions and to forecast economic activity.

### ***1.1.2 How is the Product Account Structured***

The main concerns for the government at the time that the Product Accounts were created were overall level of activity in the economy, inflation, and unemployment. The most commonly used measure of activity in the economy is currently Gross Domestic Product (GDP). One method for calculating GDP is summing all of the spending in the economy. GDP is traditionally split into four main categories, consumer spending, business spending, government spending, and foreign spending.

The consumer sector is the largest sector of the economy, accounting for nearly 70 percent of the economy. This sector is also thought of as the consumption sector. The business sector, or investment sector, is made up of residential investment, nonresidential investment, and changes in private inventories. Lastly, foreign spending can be described as net exports. More detail on the structure of the individual components is laid out later in the paper.

## **1.2 What is a Neural Network**

While the ordinary least squares model is a linear model, the artificial neural network (ANN) gains predictive power from the fact that it is non-linear in nature. Several proofs exist to show that one specific type of ANN, a multiplayer perceptron (MLP), is a universal function approximator (Swingler, 1996). This is an important fact, because it means that neural networks are capable of behaving just like linear models, but can also accommodate much more complex, nonlinear models.

### ***1.2.1 Neural Network Fundamentals***

Neural Networks can be thought of in a very similar way to an ordinary least squares regression. Both are functions, meaning that any distinct set of input variables creates a unique output variable. Like regressions, neural networks can be used to model relationships that can be represented numerically. In addition, both a regression and a back propagation neural network are proven to minimize the error in such relationships. However, the two models accomplish the feat through two different means. Regression accomplishes modeling through the use of linear models, while neural networks are proven to be universal function approximators, possible of modeling functions of any arbitrary function type (Faussett, 1994). As mentioned earlier, this is important because, in theory, this means that a neural network can perfectly model a linear model, if that is in fact the true form, but is also capable of modeling more complex relationships as well.

Like ordinary least squares regressions, neural networks have to have the coefficients of the model determined by the data the model is meant to fit. After a model is trained, the model can be used to predict output, given a set of inputs. First, the method of calculating the output given a set of inputs is described, and then a brief overview of the training process is described.

The process of calculating the output, given a set of inputs can be quite complex, and as such, it makes more sense to walk through an example of how the neural network works. Consider the network shown below in Diagram 1. The network below will be used throughout this example. It contains one input layer, one hidden layer, and one output layer.

DIAGRAM 1

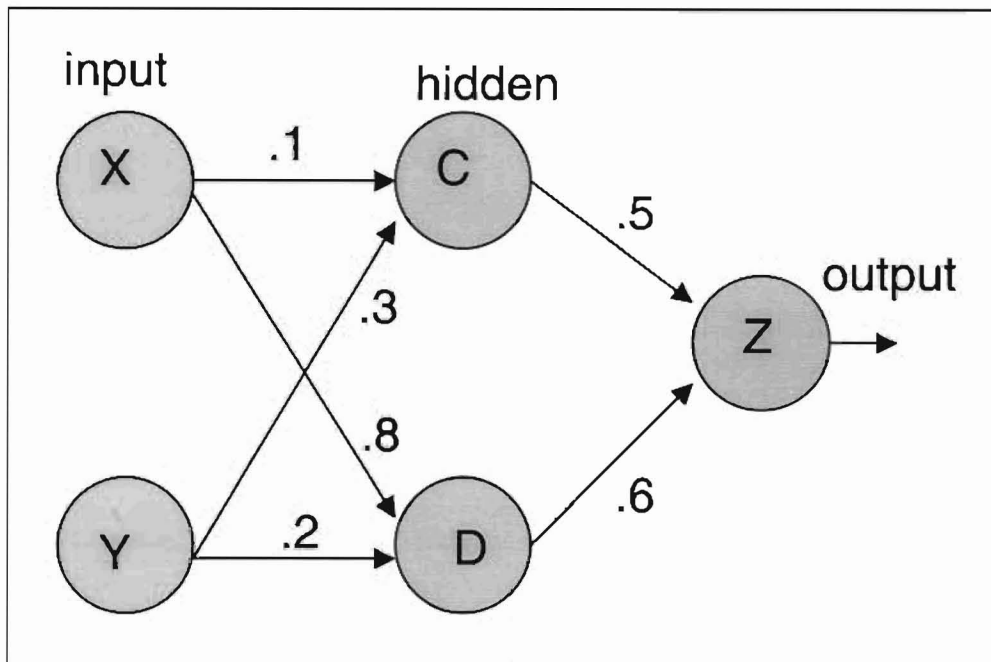


Diagram 1 shows a trained neural network (above). The name of each layer is listed above said layer. In addition, each of the weights is shown.

In the network shown in diagram 1 is of the form  $Z=f(x,y)$ , the output is a function of two input variables. Tracing one set of inputs through the network, let us assume that the data that goes into node X is the value 0.6, and the value that goes into node Y is 0.1. These values are the values from a given observation, in the two variables (X,Y) being used to predict the output variable (Z).

The values that will be passed out of node C and D are calculated through two steps. First, multiply the values from the previous layer by the respective weights and sum them. Second pass the obtained value through an “activation function,” F, such as the sigmoid  $f(x) = (1 + e^{-x})^{-1}$  in order to scale the values into a range such as zero to one. Activation functions are discussed more later. Step 1 for node C would be as follows:

$$(1) \quad F(0.1 * X + 0.3 * Y)$$

$$(2) \quad F(0.1 * (0.6) + 0.3 * (0.1))$$

$$(3) \quad F(.06 + .03) = F(.09)$$

$$(4) \quad F(.09) = \frac{1}{1 + e^{-(.09)}} = 0.52$$

Calculations for node D are analogous. In turn, Z, the output, would be calculated the same way, using the values calculated at nodes C and D as input, typically using the same function, F, as its activation function.

This use of the neural network is analogous to evaluating a regression at different points; training the network compares best to the search for the coefficient values found in the regression. In determining the values of the coefficients in a regression, all of the data is used at once, to calculate exactly what the coefficients should be. This process is essentially one step. However, in a neural network, determining the weights between layers is not as simple. This process is an iterative one, where each piece of data is considered individually. The process is as follows:

First all of the weights in the neural network are set to a small random value. Next, for each set of input values, the neural network computes the output value. It then compares the computed output to the known, actual value from the data set. Like regression, the goal is to minimize some measure of error. The error measure is chosen by the person implementing the neural network. The standard choice is the least-squares error, which is minimized by a process called the back propagation algorithm. In each step, when the computed value is compared to the actual value, the back propagation algorithm adjusts the weights in the network to bring the computed value closer to the actual, known value from the data set. This process is continued for many cycles through the data. Proofs

exist to show that back propagation networks will always converge to a minimum error given enough data and enough time.

### ***1.2.2 Finer Points in Neural Networks***

As illustrated in the earlier example, a neural network is built up of several layers, an input layer which is where the values of the data are fed in; hidden layers (just one hidden layer was used in the previous example, though more are possible) where several functions can be applied to the data as it moves through the network, and an output layer where the final result is outputted. Each layer is made up of several nodes. Each node performs several actions: first it multiplies the inputs to the nodes by their respective weights, then it sums the products, and finally puts the product through an activation function and outputs the results to the next layer. In addition, in most networks, a constant, or bias, as it is known in the field, is added to the output of the activation function. This bias (not included in the previous example for simplicity's sake) functions much in the same way as the constant in linear regressions, allowing the function to shift.

The activation function is important for several reasons. First of all, it introduces nonlinearity into an otherwise linear process allowing modeling of complex functions. Second of all, it scales the variables to keep them within a desired range. In addition, the success of the back propagation algorithm depends on such activation functions, and more particularly their derivatives. The most common activation function is the sigmoid function,  $f(x) = (1 + e^{-x})^{-1}$ . Other functions like the hyperbolic tangent function can also be used (Zhang et al, 1998). Because of the fact that these functions output values in the range of 0-1 in the case of the sigmoid, or -1 to 1 in the case of the hyperbolic tangent, variables have to be scaled down to fit into that range.



## **2 Constructing The DQEM: a Structural Model of the U.S. Economy**

The David Quarterly Economic Model (DQEM) US model was constructed to describe real Gross Domestic Product (GDPH) following the National Income and Product Accounts expenditure method for determining GDP. This method looks at consumption, investment, government spending, and net exports to determine the level of GDP.

### **2.1 GDP Measurement in DQEM: Chain Weighted**

Beginning in 1995, The Bureau of Economic Analysis (BEA) changed the accounting method behind constructing real GDP. Prior to 1995, real GDP was calculated by using a fixed base year method. According to this method, GDP would be calculated using the prices from a particular base year, in order to measure actual, or real growth, rather than nominal growth. A problem existed however; that whenever the base year changed the entire history of the series would change. In addition, the high technology sector has further complicated things. Consider the fact that in the year 2000 a low end computer retailed for over 1000 dollars, while currently, in 2004, a low end computer, with much more computing power, can be purchased for just over 400 dollars. As such, a move from a base year of 2000 to 2004 would cause a shrink in the low-end computer sector in 2000 by over 50 percent. Such rapid price changes have been regular occurrences in the high tech industry. The new chain weighing system addresses these issues by constructing GDP for a given year using the prices for current year, and the previous year. Essentially the base year is changed every year, using a moving window (Steindel, 1995).

While the chain weighting fixed the problems that it was designed to alleviate, the traditional identity that GDP equals the sum of consumption(C), investment(I), government spending(G) and net exports(NX) no longer holds in real terms. For simplicity's sake, as well as to aid in the recreation of the model in a neural network framework, this model uses the traditional identity to predict chain weighted real GDP. The discrepancy between the actual GDPH series, and the sum of C,I,G, and NX varies between 3 and 5 percent of GDP over recent years. In addition, in other places throughout the model steps have been taken to ensure a model with a small enough size to approximate the same model with a structural neural network.

In estimating equations, all equations that suffered from serial correlation were corrected with an AR (1) term, unless otherwise noted. An instrumental variable estimation was used to eliminate the simultaneity bias that would have otherwise been present in the structural model. In addition, a decision rule was used when choosing instruments for a given equation. The instruments for a given equation were the constant, a lag of all of the right hand side (RHS) variables, in the form they appear in the equation, and all other contemporaneous variables, which do not appear in the equation. The only exception is that the 30-year mortgage rate, for which data doesn't exist earlier than 1971, was excluded from the list of instruments if the fit period needed to go back further than that year. Also, in the term structure equations for the interest rates, other contemporaneous interest rates were not used as instruments. Real dollar values are chain-weighted to 1996. In addition, estimation results for all equations are in Appendix A1.

The functions that govern the dynamics of the DQEM are rather complex. These relationships can be more easily visualized using a chart. The chart below shows a high level look at the structural model.

Figure 1- Flow chart of the economy

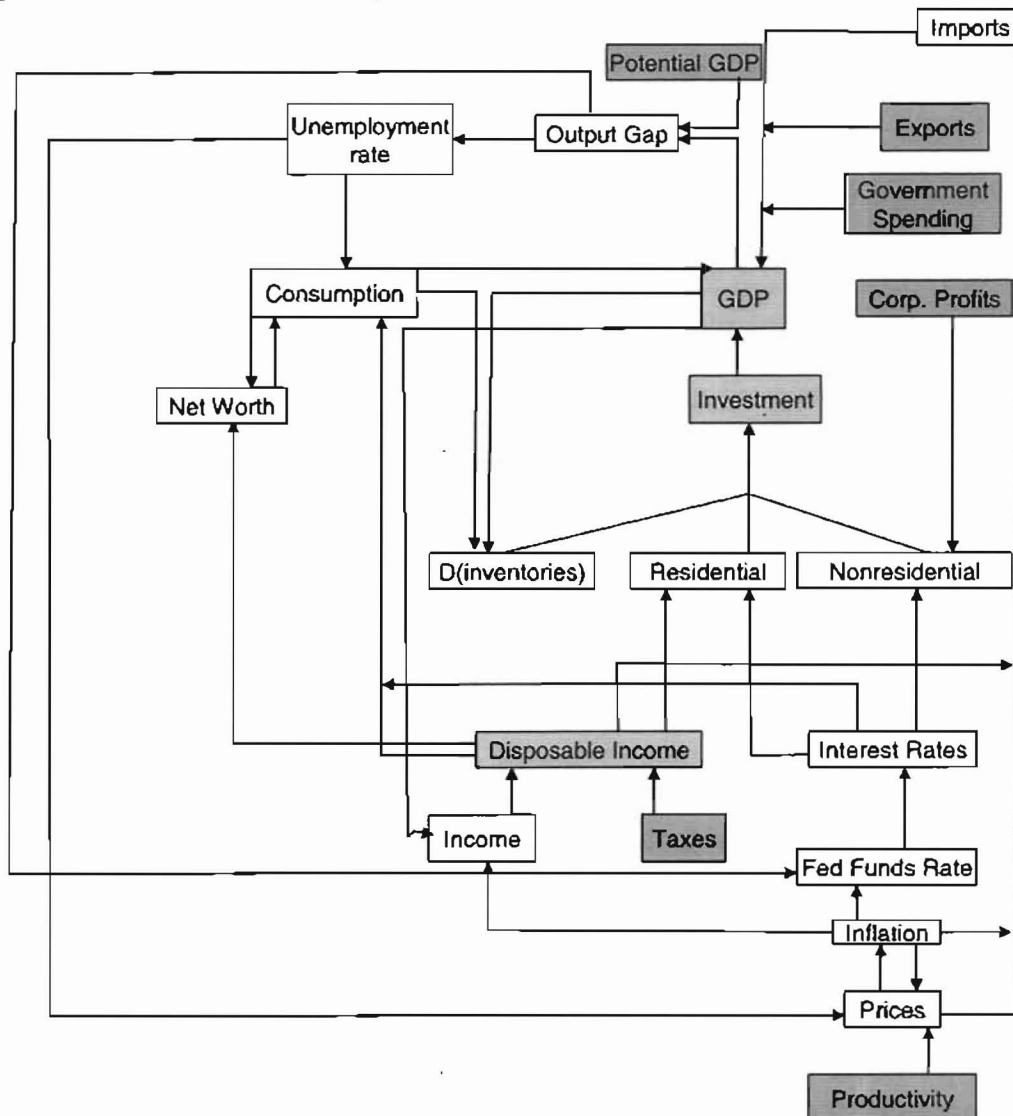


Figure 1, above, shows the relationships present in the structural model. White boxes are endogenous variables. Light grey boxes represent identities, while dark grey variables represent exogenous variables.

## 2.2 Consumption

The structure of the consumption sector is relatively simple. Rather than disaggregate consumption into durable goods, nondurable goods, and services, consumption is treated as one entity. This aids in keeping the overall size of the model relatively smaller. In addition, the model presented is similar in nature to the error correction model presented in Davis and Palumbo (2001). The idea behind this model is that people wish to consume at the same level over their lives. Fluctuations in consumption stem from people being off of their ideal consumption path, and are attempting to get back on their ideal path. In their paper, Davis and Palumbo calculate a lifestyle consumption path, and the errors from said path. While the deviations term from the lifestyle model is not used in the consumption, other variables are included to help explain these short run fluctuations.

Real consumption is influenced by consumption in the previous period, because of some market inertia that exists.

The five-year interest rate (FCM5), in the form of the five-year constant maturity note, is included to capture the interest effect that is seen in a durable goods market. Often for durable goods, such as cars, consumers borrow to finance the good. In addition, since the decision to buy a good that is expensive enough to warrant financing, it is also likely to warrant some discussion about whether or not the purchase should happen at all. Therefore, as interest rates increase, the price of the good will get relatively more expensive, *ceteris paribus*. This means that it is expected that the FCM5 will have a negative sign. It is appropriate to use a lag of the interest rate, capturing the effect that it takes time to make this decision.

In addition, the interest rate plays the role of measuring the opportunity cost of spending money. When a person chooses to spend money, he is also choosing to not invest the money. Therefore, a higher interest rate makes it so that it is more desirable to invest money, and forego consumption.

Real net worth is included to capture spending from previously acquired wealth. Because net worth is reported on a nominal basis, it is deflated by the Personal Consumption Expenditures price index (JCZ). It is expected, that accumulated wealth will cause a higher level of consumption.

Goods and services have most of their drive from contemporaneous real disposable income (YPDH). As people have more money to spend, one would expect that they would spend more money. As such, it is expected that YPDH will have a positive influence.

A lagged unemployment rate (LR) is used as a measure of how consumers feel. If the previous period has a high unemployment rate, then consumers will likely feel like their job might be at risk. People who fear they might be out of work soon will, all else being equal, spend less money than someone who believes they will be employed in future periods. Furthermore, people base their expectations on past information. In reality it is past changes in unemployment that are likely to concern workers. One would expect that last period's unemployment rate would have a negative sign.

Lastly, logs of real consumption, real disposable income, and real networth, or wealth were used, rather than the simple values. The DLOG functional form serves a very specific function. Because of the similar upward trends in consumption, wealth, and disposable income there could be a problem with co-integration. When regression

variables are co-integrated it can lead to spurious regressions, where the statistical value of variables can be overstated. The DLOG functional form is known to address this problem.

All variables are significant at 0.5 percent level, except for net worth, which is significant at the 5 percent level. The final equation used for consumption was estimated over the time period of 1958q1 to 2002q4 in the following form:

$$\text{DLOG}(\text{CH}) = 0.005 + 0.404 * \text{DLOG}(\text{YPDH}) + 0.056 * \text{DLOG}(\text{networth}) + \\ -0.004 * \text{D}(\text{FCM5}(-1)) + -0.007 * \text{D}(\text{LR}(-1))$$

## **2.3 Investment**

The investment sector is broken down into three distinct sub-sectors, each with its own characteristics. Residential investment generally reflects actions by individuals, while nonresidential investment takes place in the corporate setting. These facts are taken into consideration when constructing models for these sub-sectors. Lastly, the inventory stock is considered in a stock adjustment model.

### ***2.3.1 Residential Investment***

The residential investment sub-sector shows the amount of money being invested in residences. Investment into houses is a decision that is generally made by individuals and families. As such, the model of residential investment reflects things that a person might look at when considering whether to build, or renovate, a home.

When looking to finance residential investment (FRH), particularly, the construction of new houses or major renovations, often individuals look to use a 30-year mortgage in order to finance the purchases. Naturally as the mortgage rate (FCM) gets higher, it becomes more expensive to finance investment, and so less investment will occur. Since

a decision to build a home, or to renovate is likely to take some time, a lag of the mortgage rate is used, rather than the contemporaneous rate.

Real personal disposable income (YPDH) makes sense for several reasons as an explanatory variable in the equation. Real disposable income is needed for down payments as well as monthly finance payments. Because of this, *ceteris paribus*, if we see a decrease in disposable income, it is likely that a decrease in residential investment will follow.

In estimation of the model, it was determined that serial correlation was a problem. In fixing this problem, the equation was transformed to a first difference equation. Even after the first differencing, it appeared as if the equation still suffered from serial correlation, and so this was corrected using an AR (1) correction, as well. Furthermore, the equation is in a double log form, where residential housing and YPDH are both logged. Both variables were significant at the 0.01 percent levels. The final equation was of the form and estimated over time period of 1972q1 to 2002q2:

$$DLOG (FRH) = -0.007 + 1.364 * DLOG (YPDH) + -0.055 * D(FCM (-1))$$

### ***2.3.2 Nonresidential Investment***

Corporations fuel nonresidential Investment, though some of the same logic applied to residential investment can be applied. Nonresidential investment includes things like software and computers, structural improvements, as well as new plants and equipment.

When looking to finance nonresidential investment (FNH) corporations generally finance their investment with corporate bonds. Moody's AAA bond rate is thus a good indicator of the interest rate that corporations can borrow at to finance their investment.

As this interest rate goes up, all else being equal, it is likely nonresidential investment will fall.

The profit that a corporation makes is the money that the company can use to spend on investment. Whether it be in paying interest on loans, or paying for the entirety of a project, corporate profits (YCP) are necessary. Therefore, as corporate profits rise, more companies will be able to afford investment projects, as such we would expect a positive sign on the corporate profits variable.

While residential improvements require some discussion, and thus there is a one period lag on the interest rate, it takes substantially longer for corporations to decide to undertake, and actually finish investment projects, as such; both variables are lagged three periods, illustrating this. In addition, last quarter's nonresidential investment is included. In addition, the nonresidential investment series looked as if an exponential function would fit better than a linear, so FNH as well as its lag was logged. All variables are significant at the 5 percent level in one-tailed tests. The final version of the equation was estimated between 1982q1 and 2002q2 in the following form:

$$\begin{aligned}\text{LOG (FNH)} = & 0.811 + 0.00016 * \text{YCP}(-3) + -0.005 * \text{AAA}(-3) \\ & + 0.873 * \text{LOG (FNH (-1))}\end{aligned}$$

### ***2.3.3 Change in Private Inventory Stock***

The last part of investment that needs to be modeled is the change in inventory stock, or inventory investment. Inventory changes must be accounted for in the expenditures method for calculating GDP because when a firm builds up inventories, they are producing but consumers aren't purchasing the goods. As such, it is almost like the firm is buying their own goods, to be used to sell to consumers at a later date. Rather than



model the change in inventories, the level of inventories (SH) is estimated, and the change is calculated by subtracting the inventories of the last period from the inventories from current period. Inventories are modeled by stating that this period's level of inventory is equal to last period's level plus the adjustment this period.

Inventories are excess production. This can be modeled simply enough using consumption and output; excess production is output less consumption. Therefore we would expect that all else held equal, as production goes up, inventories goes up. Also, we would expect that as consumption goes up, inventories would go down. All variables are significant at 0.01 percent level in a one tailed test. The final version of the equation was estimated between 1958q4 and 2002q2 in the following form:

$$SH = -8.539 + 0.121*GDPH + -0.128*CH + 0.797*SH (-1)$$

## **2.4 Net Exports**

Net exports are defined as the difference of imports and exports. Imports to a given country are determined by conditions in that country. Therefore, imports to the United States can be modeled using U.S. indicators, however exports of the US are functions of rest of world indicators. In order to maintain a relatively small model, real exports are treated as exogenous, keeping the rest of the world out of the model.

### **2.4.1 Imports**

Imports share some similarities to consumption. After all, imports are merely goods purchased from other countries, to be used or sold within the borders of the United States. While the government can purchase from foreign countries and investment can occur with foreign goods, since nearly 70 percent of economic activity comes from the

consumption sector, it made sense to model imports more similarly to consumption<sup>1</sup>. The variables included reflect this.

Some imports, such as automobiles are frequently paid for over time, as such, a five-year interest rate is included to capture the price of financing. However, like in the consumption sector, decisions to purchase items that require financing are often thought about for a while, so the interest rate is lagged. It follows that as the financing cost goes up, imports will go down, so it is expected that the interest rates have a negative impact on imports.

It follows quite naturally, that as the relative price of imports goes up, imports will drop. As such, an import price (JM) was included to capture this effect. While ideally, this would be a comparison between U.S. prices and the rest of world price of goods, it wasn't practical to do in this situation. It is worth mentioning that this approach was taken, as it is simpler than a foreign sector that would rely on an actual exchange rate.

Lastly, personal disposable income is included to capture the amount of money consumers have to spend. As income increases, all else being equal, consumers will buy more, and thus import more.

In addition to the above, a lag of last period's imports was included to capture the inertia in the market. All variables are significant at the five percent level of confidence in one-sided tests, except for interest rate, which was significant at the ten percent level of confidence. Serial Correlation was not a problem. The equation was estimated as a double log equation over the period of 1960q1 to 2002q2 in the following form:

---

<sup>1</sup> This value was calculated from the latest GDP press release.

$$\begin{aligned}\text{LOG}(\text{MH}) = & -1.029 + 0.916*\text{LOG}(\text{MH}(-1)) + 0.204*\text{LOG}(\text{YPDH}) + \\ & -0.029*\text{DLOG}(\text{JM}) + -0.002\text{FCM5}(-1)\end{aligned}$$

## 2.5 The Price Sector and The Phillips Curve

### 2.5.1 The Price Sector

The Phillips curve relationship is used to give an inflation rate based on the Personal Consumption Expenditures (JCZ). In this model of the economy there are three price indices that are used. The first is the Personal Consumption Expenditures Price Index, mentioned before. This price index is used as the primary price deflator in this model.

The second is the gross business product price index (JGDPB). This measure of price is in the model since the Federal Reserve Board often uses this in order to make decisions about interest rates.

The third is the consumer price index, less food and energy (PCUSLFE). This index is used in the Phillips curve, as a price parity term between the U.S. and the rest of the world. The rate of growth of this price is compared with the rate of growth of an exogenous imports price variable (JM) in this inflation difference term. This term variable also shows up in the imports equation in a relative price term.

The consumer price index and JGDPB are each modeled from the inflation term predicted from the Phillips Curve relationship. Both are modeled using the assumption that price levels in the economy will change in roughly the same manner. Both are modeled using a first difference equation, where the first difference of each variable is modeled off the first differences of JCZ as well as one lag of the first difference of JCZ. Both of these terms are significant at any level and take the form:

$$D(\text{JGDBP}) = 0.002 + 0.590*D(\text{JCZ}) + 0.358*D(\text{JCZ}(-1))$$

$$D(PCUSLFE) = 0.185 + 0.945 * D(JCZ) + 0.489 * D(JCZ(-1))$$

### 2.5.2 *The Phillips Curve*

The Personal Consumption Expenditures Price Index (JCZ) is calculated from last period's index level as well the rate of growth calculated in the Phillips Curve. However the Phillips curve also expresses the relationship between inflation and the unemployment rate. A.W. Phillips originally laid out the Phillips curve relationship in 1958, though the relationship modeled here is actually a derivative of the original relationship, refined by Donihue and Foote (Donihue and Foote, 1995). It has to be mentioned that throughout his works, Fair disagrees with this approach. Specifically, Fair points out in his work that inflation and unemployment are simply two separate macroeconomic variables, and there is no reason to assume that a stable relationship will exist between them (Fair, 1978). Despite his objections, a Phillips Curve relationship will be used to incorporate price levels into the model.

This particular Phillips Curve is based on adaptive expectations, meaning that people expect future values of inflation to be similar to past values. The Phillips curve relationship state that inflation is a function of expected inflation, the unemployment rate, productivity growth, and inflation parity between the U.S. and the rest of the world.

In the long run, expected inflation should be equal to contemporaneous inflation. In order for this to happen econometrically, the coefficient on expected inflation should equal one. Nine lags of inflation (via the rate of growth of JCZ) are included. The coefficients on the nine lags sum to a value that is not statistically different from one. This means that in the long run, the Phillips curve is vertical.

The crux of the Phillips curve relationship is that inflation and unemployment are inversely related. As such it goes without saying that the unemployment rate must be in model. However, an additional piece is also included, the rate of growth of productivity (LXNFAROG). This is included because increases in productivity should have a similar effect as hiring more workers. Both more workers, and higher productivity will, *ceteris paribus*, lead to more output. Therefore, it is expected that inflation will be inversely related with both the unemployment rate, as well as the rate of growth of productivity.

In the long run, the inflation gap between the U.S. and the rest of the world will be equal to zero. This parity condition is calculated through the use of an import price (JM) and a U.S. goods price index (PCUSLFE). Since in the long run, these two values have to be equal, if foreign inflation is above U.S. inflation than one would expect U.S. Inflation to rise, to bring the parity back.

Lastly, as discussed by Robert Gordon, Nixon's price controls interfere with the relationship (Gordon, 1990). As such, the time period when the price controls are imposed (Nixon), as well as when they are removed (Nixoff) are noted by dummy variables.

The regression was estimated from 1958q4 to 2002q2. All variables, except for Nixoff are significant at the two percent level, in a one tailed test. Furthermore, the expected inflation coefficients are not significantly different from one. The model was estimated in the following form<sup>2</sup>:

$$\begin{aligned} \text{Inflation} = & C_{\text{phillips}} + \beta_1 \text{Expected Inflation} + \beta_2 \text{Lxnfarog} + \beta_3 \text{Nixon} + \beta_4 \text{Nixoff} \\ & + \beta_5 \text{LR} + \beta_6 \text{Inflldiff} + \varepsilon_{\text{phillips}} \end{aligned}$$

---

<sup>2</sup> Due to the number of lags used for the Expected Inflation term, it is not practical to show the results here. However, all results are shown in Appendix A1.

## 2.6 Okun's Law For Determining Unemployment Rate

Okun's law states that there is a relationship between the unemployment rate and the gap between potential output and actual output. The theory behind this is that in order to obtain potential GDP the economy must be working at full capacity. Therefore, the closer the economy is to its potential level, the lower the unemployment rate. For the purpose of this model, the gap is created by dividing real GDP by the potential GDP. When the gap is above one, it means that output is higher than potential, signifying that a pullback should be coming, and that the unemployment rate should be rising. In order to construct this model, three lags of the output gap as well as a lag of unemployment rate are used. The final model was estimated from 1958q4 to 2002q2. The output gap variables are all significant at the ten percent level of significance, and the lag of unemployment is significant at any level. The final form of the equation follows:

$$Lr = 0.609 + 0.896*LR(-1) + 0.005*Outputgap(-1) + 0.006*Outputgap(-2) \\ + 0.005*Outputgap(-3)$$

## 2.7 The Term Structure and Federal Funds Reaction Function

The federal funds reaction function is used to predict the level of the effective fed funds rate. All other interest rates in the economy are based on this rate. The fed funds rate (FFED) is determined, at least in part by the Federal Reserve Board, so reaction function should model the policy rules that the board follows. It has been shown that while no such true rule exists, the Greenspan board decisions can be described well by the Taylor rule(Woodford, 2001). This model is a customized Taylor rule. The model states that the fed funds rate is based on last quarter's rate, as well as the rate of growth of jgdpb, a business price index, and an output gap.

The first measure included is one of inflation in the business sector. The current Federal Reserve board looks very closely at this particular definition of inflation, as it is believed that business spending is what drives the economy. Therefore, this factor is considered when deciding on the course to take, as far as raising and lowering interest rates.

In addition, the output gap is a good way to measure how “hot” the economy is. This Federal Reserve board has been very focused on inflation. An economy that is operating above potential will, all else being equal, have a high inflationary pressure. Therefore, this would most likely cause an increase in the interest rate.

In the estimation of the model all variables were significant at the one percent level. The model was estimated between 1971q2 and 2002q2 in the following form:

$$Ffed = -13.055 + 0.883 * Ffed(-1) + 13.419 * Output\_Gap + 0.149 * Rogjgdpb$$

### **2.7.1 The Term Structure**

The term structure describes the interest rates of the model. All interest rates in the model are built off of the effective fed funds rate. The FFED is used directly to calculate the 6-month t-bill. The five year rate is calculated using a lag of itself and the six month t-bill. The ten year rate, and the 30 year mortgage are calculated in the same way, except the ten is based on the five, and the 30 is based on the ten. Lastly, Moody’s AAA corporate bond interest rate is based off of the ten-year rate.

## **2.8 Income Sector**

Personal income plays a part in nearly every sector of the economy. Any sector where consumers are involved is partially driven by income, and more specifically personal

disposable income (YPDH). Also in this section is another stock adjustment modeled variable, net worth, is discussed. These equations are included to complete the model, and don't rely particularly heavily on theory.

### ***2.8.1 Personal Income***

Personal Income is closely related to GDP. This is not surprising since in order to produce output, firms must pay wages to their workers. In addition, nominal personal income (YP) is related to price growth. The change in prices is included to explain phenomena like cost of living increases in wages. It is expected that, as prices grow, wages will follow. The model is estimated in a double log form, and both variables are significant at the five percent level of significance. The relationship was estimated between 1958q4 and 2002q2 in the following form:

$$\text{Log (YP)} = -0.450 + 1.031 * \text{Log (GDP)} + 0.006 * D \text{ (JCZ)}$$

### ***2.8.2 Personal Disposable Income***

Disposable income, as reported by the Bureau of Economic Analysis, is calculated through an identity that states that personal disposable income is equal to personal income minus personal taxes (YPX). This identity is used to compute personal disposable income in this model.

### ***2.8.3 Household Net Worth***

Household net worth is treated as a flow type variable in the model. What this means is that the current period's net worth should be equal to last periods plus a change. The form of the equation quite intuitively follows this. We would expect that net worth from last period will be close to net worth in this period, meaning that the coefficient should be near one, but not equal to it. The fact that it is less than one, follows from the fact that in



other sectors of this model it has been suggested that people might spend some of their net worth for certain types of purchases.

In addition, personal disposable income (YPD) is used as the basis for the period-to-period changes in net worth. This personal disposable income effect is used to model the fact that people save some of their disposable income, thus increasing their net worth. All variables were significant at any level. The model was estimated between 1958q4 and 2002q2 in the following form:

$$\text{Net\_worth} = 22.358 + 0.975 * \text{Net\_worth}(-1) + 0.194 * \text{YPD}$$

## 2.9 Completing the Model: A List of the Identities

In addition to the several different regressions used to model the economy it was also necessary to use a few identities.

### GDPH makeup:

$$\text{GDPH} = \text{CH} + \text{GH} + \text{MH} - \text{XH} + \text{FRH} + \text{FNH} + \text{SH} - \text{SH}(-1)$$

### Deflators:

$$\text{GDP} = \text{GDPH} * (\text{JCZ}/100) : \text{JCZ is used since it is the primary price driver}$$

$$\text{Net worthh} = \text{net worth} * (\text{JCZ}/100)$$

$$\text{YPDH} = \text{YPD} * (\text{JCZ}/100)$$

### Rates of Growth:

$$\text{lxnfarog} = ((\text{lxnfa} / \text{lxnfa}(-1))^4 - 1) * 100$$

$$\text{rogjgdpb} = ((\text{jgdpb} / \text{jgdpb}(-1))^4 - 1) * 100$$

### Output Gap:

$$\text{Output Gap} = \text{GDPH}/\text{GDPPOTH}$$

### Level of JCZ:

$$\text{jcz} = \text{jcz}(-1) * (1 + (\text{rojcz} / 100))^{.25}$$

### Inflation Parity between U.S. and the Rest of the World

$$\text{infldiff} = ((\text{jm} / \text{jm}(-1))^4 - 1) * 100 - ((\text{pcuslfe} / \text{pcuslfe}(-1))^4 - 1) * 100$$

### Disposable Income Identity

$$\text{YPD} = \text{YP} - \text{YPX}$$

### **3 Stuctural Neural Network Construction**

The neural network is supposed to mimic the structure and relationships expressed in the structural macroeconomic model. As such, it makes sense to pursue the construction of the neural network in the same manner that one constructs the structural model. The neural network will simply be replacing the mathematical equation as the method for describing each function.

Each of the relationships in the structural model needs to be recreated using neural networks. As such there will be 31 networks that will be trained separately, and then connected to form a larger model.

#### **3.1 Modifications to the Model for use in the Neural Network**

From the beginning of implementing the structural model using neural networks, the question of theoretical and physical limitations that neural networks and the chosen software for implementing neural networks, JOONE, impose has needed to be answered. The first and most notable limitation is a theoretical one.

The issue of recurrent networks is the first to tackle. Recurrence in neural networks, translates to the notion of simultaneity in mathematical systems. While fully recurrent networks have been shown to converge (Faussett, 1994), it is not clear that partially recurrent networks, such as those needed for a structural model will converge. Furthermore, it is also difficult to interpret the meaning of a recurrent network. Furthermore, in a more practical problem, JOONE seems unable to deal with recurrency in the model. For this reason the model was modified to remove all simultaneity.

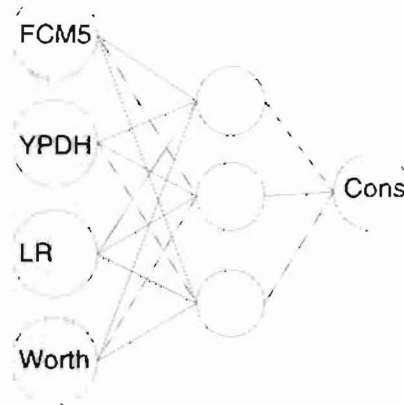
In order to remove the simultaneity there were very few modifications that actually had to be made. GDP was changed to a one period lag of GDP in the inventories network and the income network. In addition, the consumer price index had to be made to be exogenous.

### 3.2 Neural Network Methodology

The larger model will be constructed of several smaller neural networks. Each of the smaller neural networks was constructed using the same rule of thumb. The number of nodes in the hidden layer of a given network was set to be  $2x+1$ , where  $x$  equals the number of inputs, or explanatory variables. Furthermore, networks had three layers, an input layer, a hidden layer, and an output layer. Networks were trained on 600,000 cycles through the dataset. Each network was trained on data between 1982:q1 and 2002:q2.

In the network shown below, consumption is a function of the five-year interest rate, disposable income, net worth, and the unemployment rate. Note that the network below is just to get a general idea of the structure, but in fact, has too few hidden nodes. According to the rule of thumb, there should be nine hidden units. A diagram of the structure of such a network is shown below.

**Figure 4 - The structure of a multivariate consumption function**



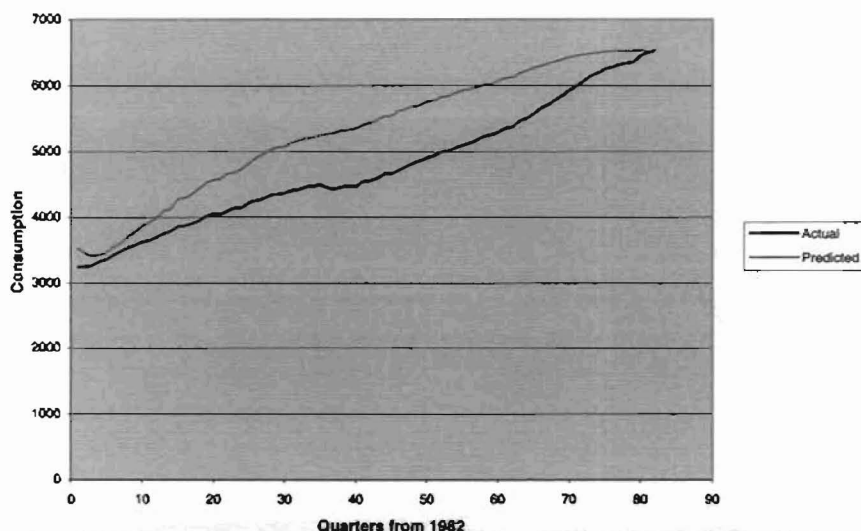
Above, figure 4 shows the structure of a network describing a consumption function.

Similarly, the unemployment rate is modeled as a function of three lags of the output gap, and last period's unemployment rate. This small network would be built up in the same way the multivariate consumption network was built. In order to “connect” the two networks, the output from the unemployment network would be fed directly to the consumption function, which calls for the input of the unemployment rate.

### 3.3 Consumption

Like most of the neural networks, the consumption network followed the same function as the consumption function in the structural model. The network has consumption as a function of FCM5, YPDH, and the unemployment rate, all of which are determined earlier in the model. The results from the neural network are shown below.

Actual Vs. Predicted

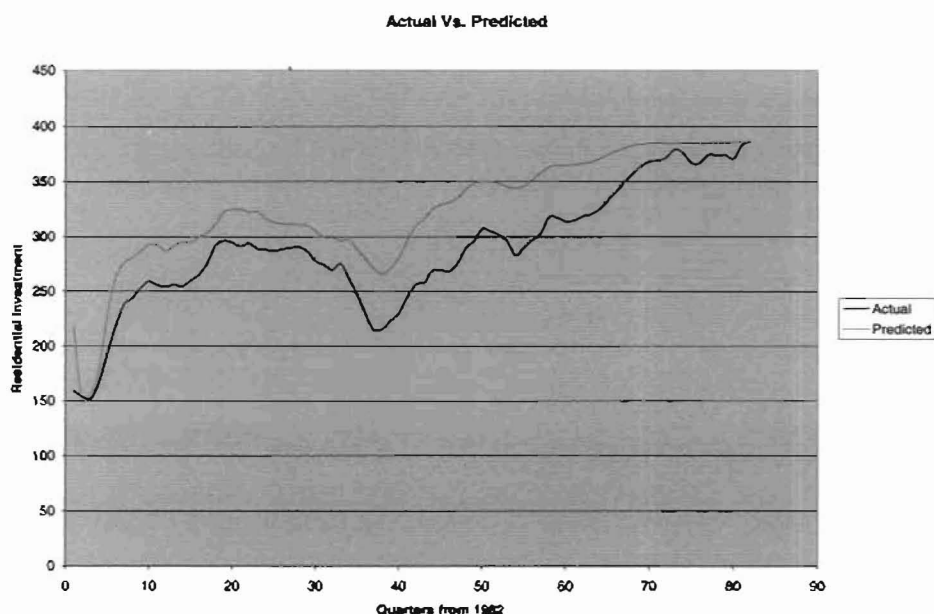


Notice that the predicted values of consumption greatly overestimate consumption throughout the time period. Because consumption is one of the last networks estimated, using other estimated values, it is possible that the over prediction comes from the over prediction of other variables.

### 3.4 Investment

#### 3.4.1 Residential Investment

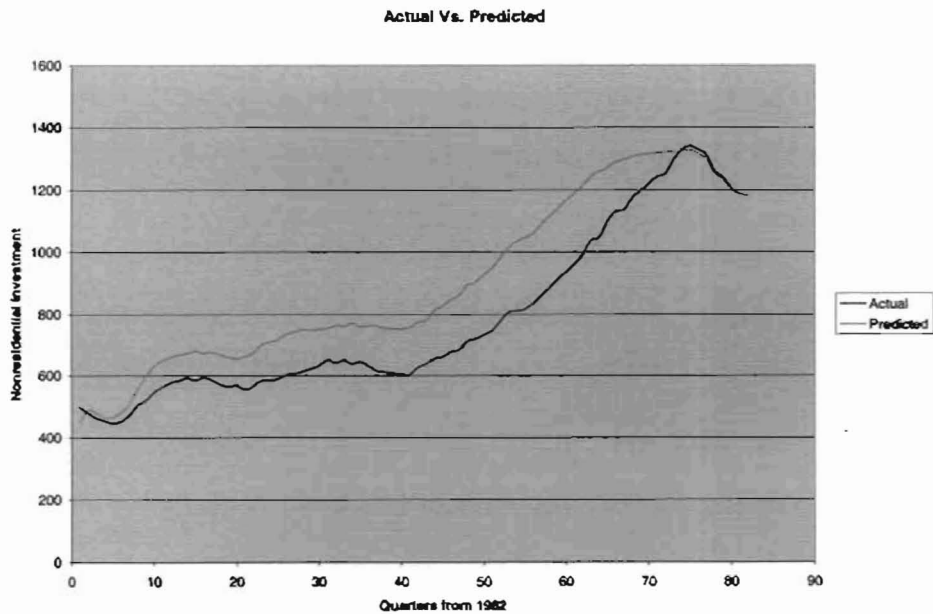
Residential investment is modeled as a function of a lag of itself, as well as a function of the 30-year mortgage rate, and personal disposable income. Results from the model are shown below:



Once again, the neural network systematically overestimates the actual values. However, other than the systematic over estimation, it appears as if the network does a good job capturing fluctuations in the variable, including turning points.

### 3.4.2 Nonresidential Investment

The network for nonresidential investment is specified in the same manner as the structural model. Similar to the residential investment predictions, there appears to be a systematic over estimate of the level of investment, while the prediction does appear to follow the dips and rises of the actual values relatively well.

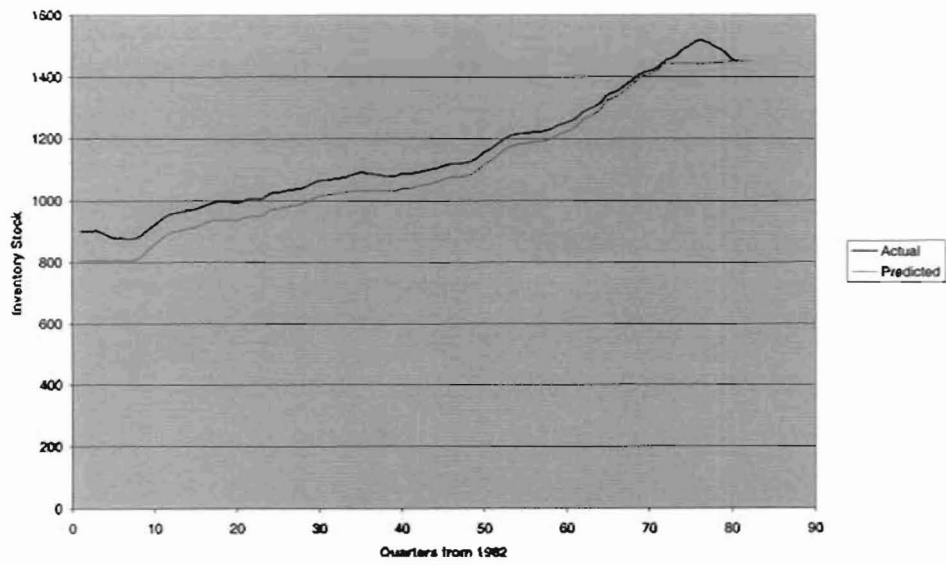


### 3.4.3 Change in Private Inventory Stock

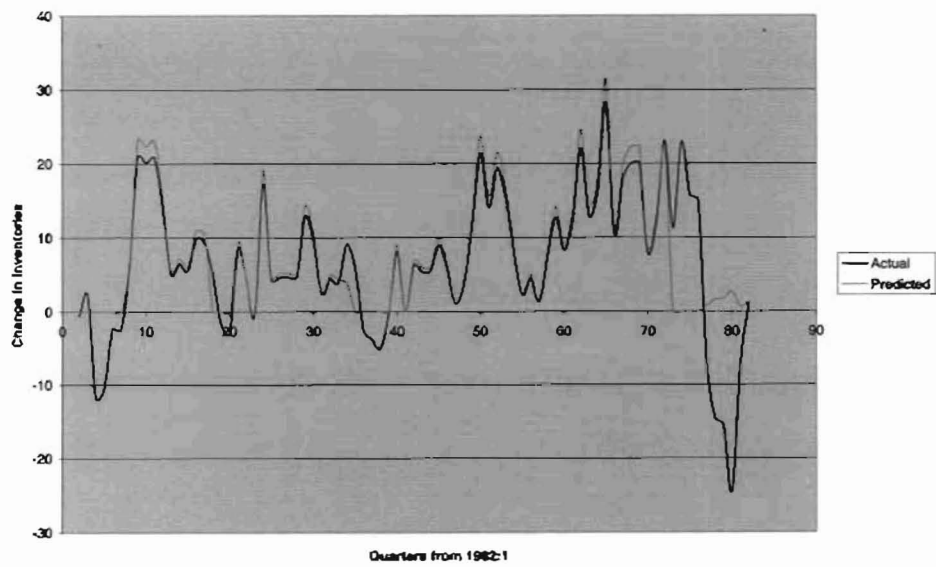
Like the other variables, the inventory stock seems to be systematically overestimated throughout the time period in question. However, the model does do a good job at predicting the changes in the inventory stock, as evident by the second graph on the following page. There is one change in this network, when compared with the structural model: GDP is lagged. Inventories are set as a function of a lag of inventories, a lag of GDP and current consumption.



Actual Vs. Predicted

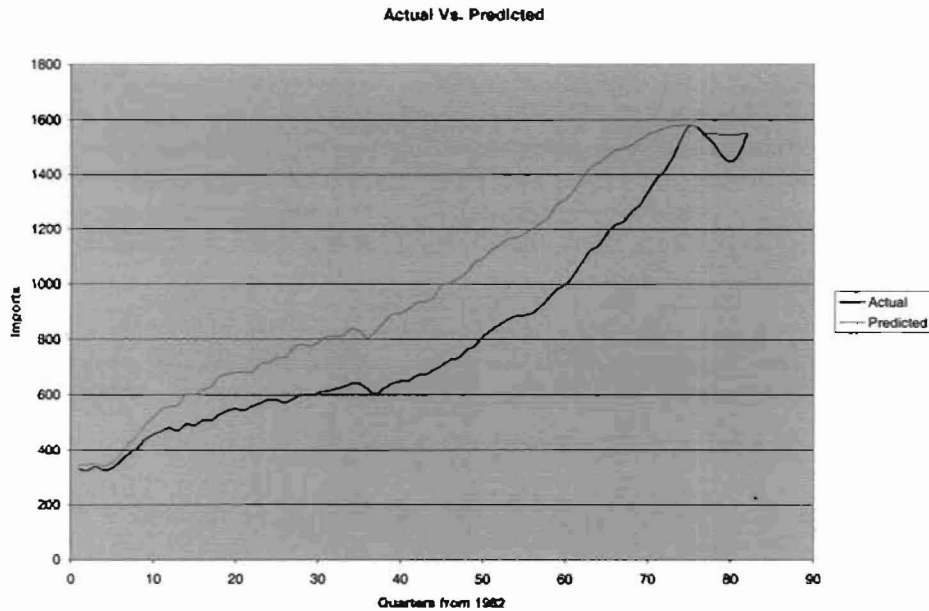


Actual Vs. Predicted



### 3.5 Imports

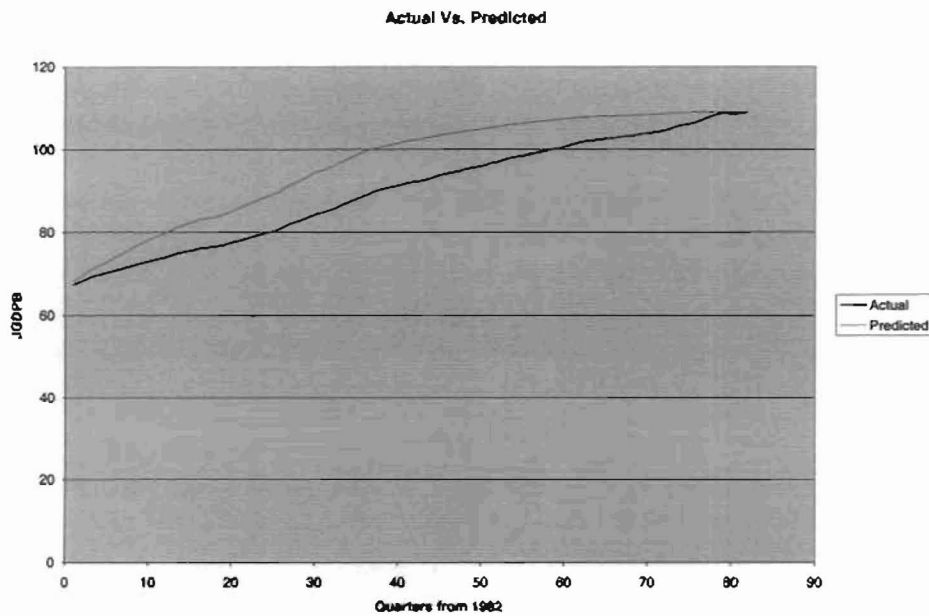
Imports follow the same pattern that can be seen in most every other graph. There appears to be an overestimate of imports throughout.



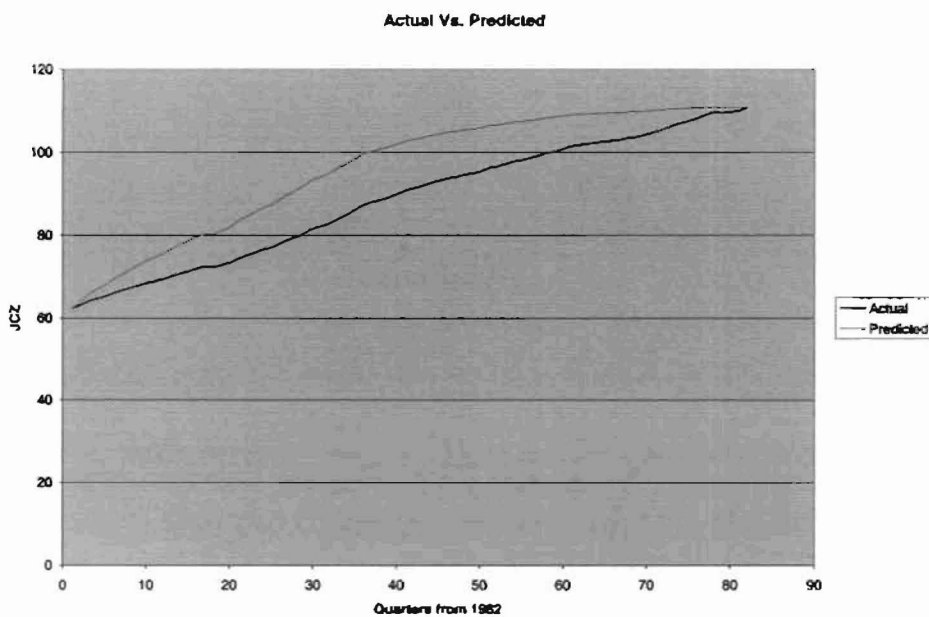
### 3.6 The Price Sector and the Phillips Curve

The Phillip's Curve introduces much of the error found in the rest of the model. While all of the other neural networks converged to extremely low errors ( $RMSE < .05$ ), the Phillip's Curve network would not converge below 0.2. This was clearly too high. I removed four of the inflation lags, leaving only five, which reduced the error to 0.1, however this is still a factor of 5 greater than most other errors. Since the prices of the model are determined from the Phillips curve, the effects of this are far reaching. Anything that is deflated, like YPD, is affected. In addition prices also affect the FFED, which in turn affects all of the interest rates. I believe that this is where at least part of the overestimates in the model comes from.

### 3.6.1 The Price Sector

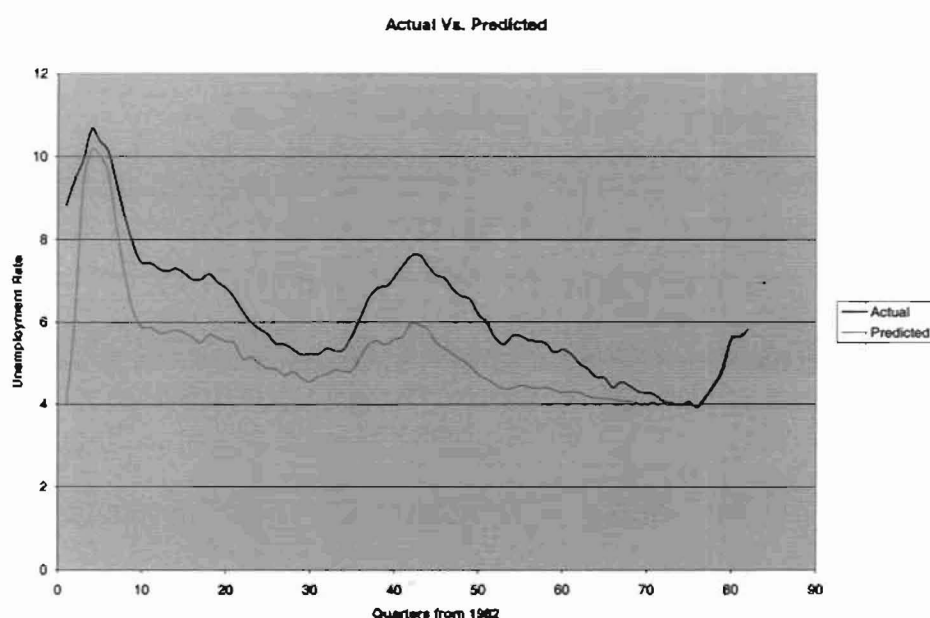


### 3.6.2 The Phillips Curve



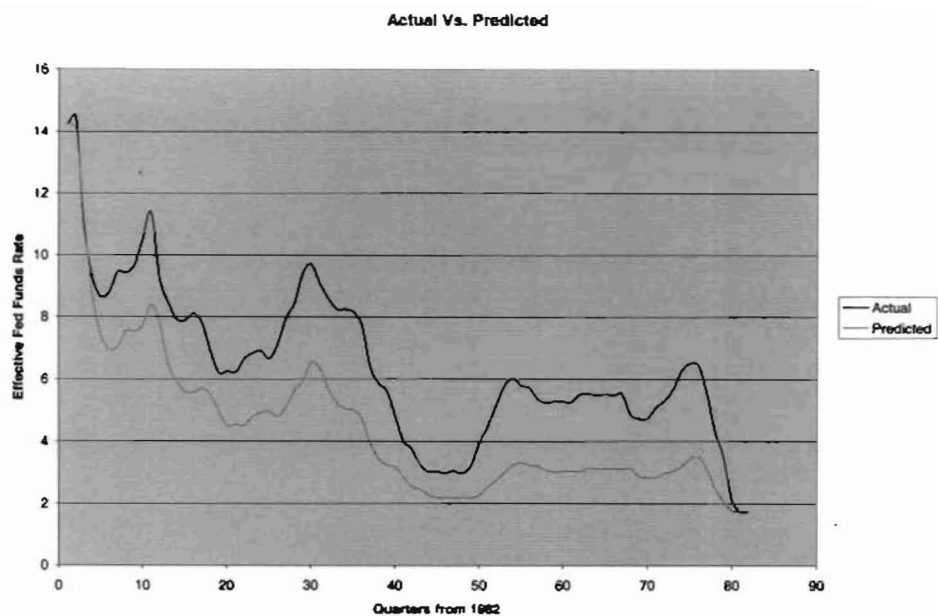
### 3.7 Okun's Law for Determining the Unemployment Rate

The unemployment rate is determined using three lags of GDPH and Potential GDP. Both of these variables are predetermined as one is a lag and the other is exogenous so no modifications were made from the previous specification. Given that many other economic measures are over predicted, it is not surprising that unemployment appears to be under predicted for most of the time period.

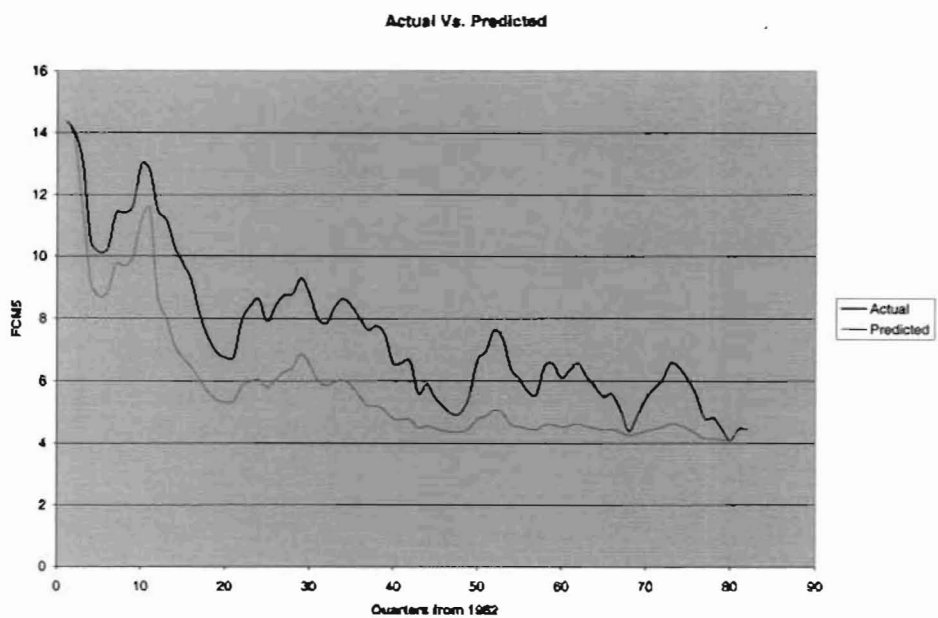


### 3.8 The Term Structure and the Federal Funds Reaction Rate

The Fed funds reaction function under predicts for the majority of the time period. This feature is then passed onto the term structure. Below are graphs from both the FFED and FCM5 predictions. It is clear that these follow the same pattern. The rest of the interest rate term structure follows a similar pattern of under prediction.



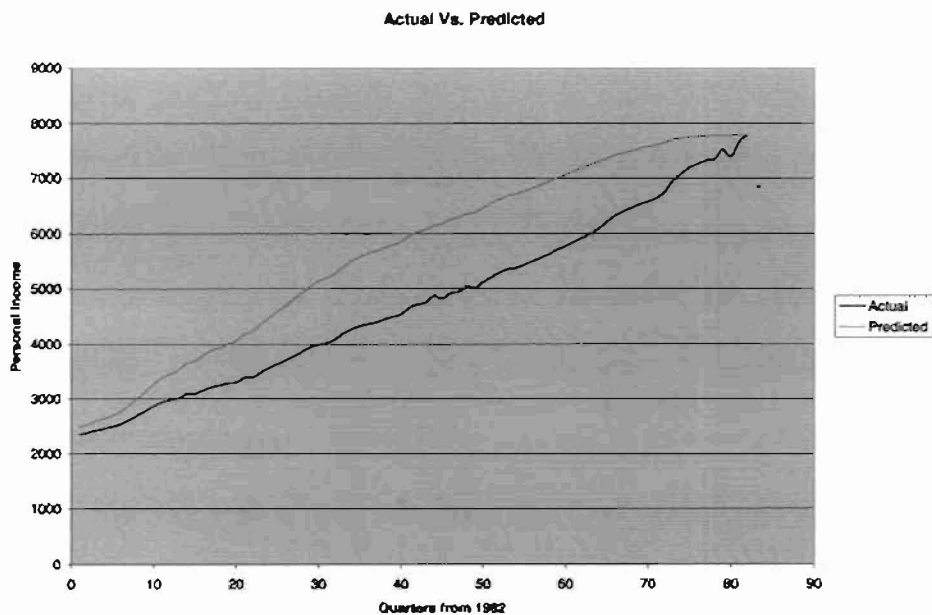
### 3.8.1 The Term Structure



## 3.9 Income Sector

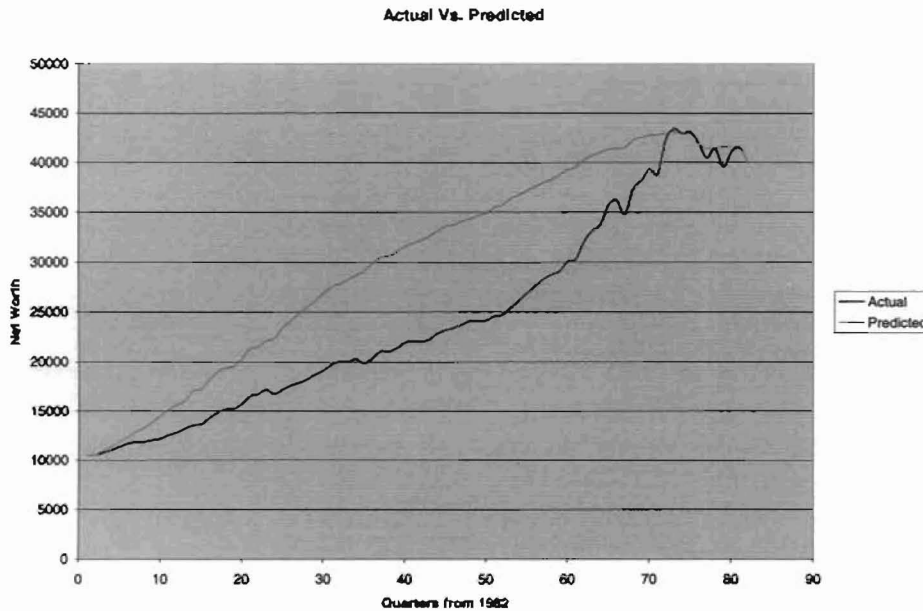
### 3.9.1 Personal Income

Personal Income is a function of GDP; however, in making the model recursive this was modified to be a lag of GDP. In addition, income relies on inflation, as contracts will be negotiated to match inflation. Below it can be seen that there is a overestimation throughout the time period.



### 3.9.2 Household Networth

Because networth is a function of income, it is not surprising that networth is overstated. Net worth is estimated to be last period's networth plus the some portion of income from the current period, which can be thought of as savings.



## 4 Comparing the Two Models

### 4.1 Exploring Determinism in Neural Networks

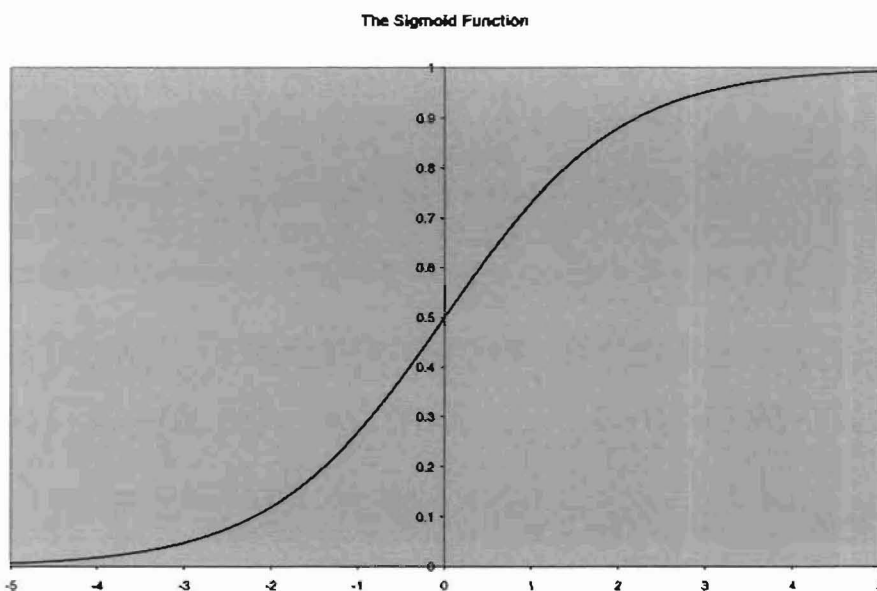
Earlier in this paper, the similarities between regressions and neural networks were explored. There are several differences as well. Probably the most important is that of determinism. Regression coefficients are based only on the data. There is nothing random in the determination of the coefficients, as such, given the same data, the same regression equation will be produced, time after time. This is not necessarily the case with neural networks. While it is provable that a network converges to its point of minimum error, in practice, networks do not necessarily reach the same point in the same manor every time.

This can partially be blamed on a lack of data, simply because neural networks perform best with extremely large datasets. It can be proven that the error of a network will be no greater than the number of weights divided by the number of observations (Faussett, 1994). In a three variable neural network, following the rule of thumb in this

paper, there would be 28 weights, meaning that in order to assure an error no greater than 0.05 or five percent, there would need to be 560 examples. One might begin to see why the Phillips Curve network, which has over 200 weights doesn't converge as closely as the other network.

However, the second part of this comes from the fact that neural network weights are initialized to small random values. These values will not be the same every time, as they are random. Because of the fact that there is not an infinite amount of data, which is theoretically necessary to reach the minimum error ( $0 = N/\infty$ ), it is not assured that the network will reach the same place in its convergence from different starting points.

There is also some question as to the choice of activation function. Below a graph of the sigmoid function, the chosen activation function is shown.



The sigmoid function, above, requires a very large number to be approximately one, and a very small number to reach approximately zero. For this reason, some people choose to scale data to a tighter range, such as 0.2 to 0.8, rather than 0.0 to 1.0 as done in the model



in this paper. Examples of this can be found in Zhang (1998) and Swingler (2001). It is possible that this difference in scaling can drastically affect the results.

## **4.2 Training and Usage times in Least Squares and Neural Networks**

A second place where there is a large difference is in the training and usage of the two types of models. In the OLS paradigm, training can be considered to be the process of calculating the regression coefficients. Each of the coefficients can be calculated directly, using mathematical equations. While these operations are complex in a multivariable regression, and requires solving a system of equations, using matrix algebra this can be completed relatively easily on a computer. In all, the time it takes to estimate every regression equation in the model is less than 10 seconds worth of computer time. Neural network training is quite different. As described earlier, each model was trained for 600,000 iterations through the data. Each run took between 6 and 8 hours to complete<sup>3</sup>.

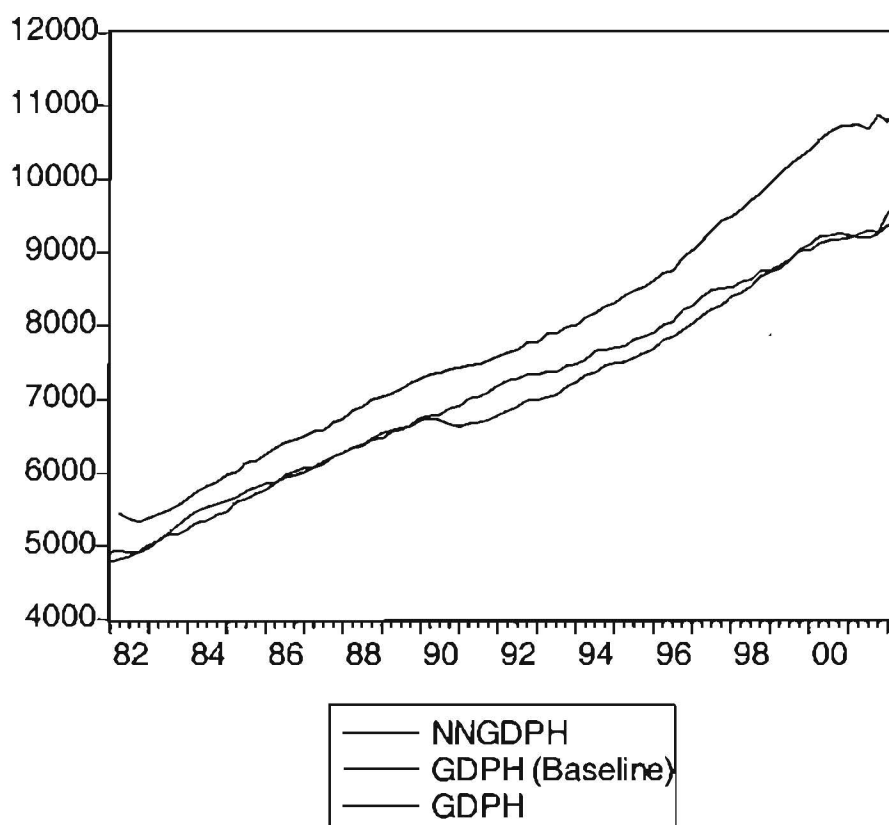
Once a neural network is trained, however, its output can be represented as a mathematical statement. While it is a rather complex statement, it is still easily computed by a computer. This computation is not vastly different from predicting values in neural networks. Both calculating the output from a regression and from a neural network take under a second of computational time.

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<sup>3</sup> The actual run time varies based on several factors. First of all, the experiments were run on a public machine, so other programs could have been using part of the computer, slowing the training down. Second of all, the number of weights in the network affects the time it takes to train.

### 4.3 Completed Models and Results

As discussed earlier there are stark differences in between the two models. Most notably, the DQEM was solved dynamically, while the neural network model was solved statically, and modified to be a recursive model. That being said, it can be seen, below, that the DQEM fits the actual values much better than the neural network results, which appear to have a level shift.



The ordinary least squares model, on the other hand, seems to perform exceedingly well. The only problem is that the DQEM seems to miss the early 90s recession. Other than that, the model tracks extremely well, never straying from actual values by more than four percent.

## 5 Conclusions

While at first glance it appears that the DQEM is a more efficient and more accurate model, there is something of interest in the neural networks. While the overall accuracy of the neural networks is somewhat low, it is interesting to note that they always track extremely well at the end of the sample. I believe that the reason for this is the following. When the neural network is being trained, the last few examples it encounters are the last examples in the time period. More precisely, the last alteration to the neural network is always to make the network fit the last data point better. This fact could prove to be useful in a forecasting scenario. However, a second way to tackle this would be to use something called batch processing during the training. Rather than train the network one observation at a time, the network would run through the entire data set once, averaging all of the errors, and make one adjustment to the network for each cycle through the data. This would make it so that the network is being fit to the entire data set, not just the end.

Secondly, while there is a large amount of error in the neural network, much of it is introduced in the Phillip's Curve network, where there simply isn't enough data to train a network that is so large. Many of the neural networks perform exceedingly well otherwise, even capturing recessions. Possibly better than either the DQEM or the neural network approach would be a hybrid approach, using neural networks for the relationships, for which it performs better than regression, and filling out the model with regression. In this way, the benefits from both neural networks and structural modeling can be realized.

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## Appendix A1: Regression Results

### A1.1 Consumption

Method: Two-Stage Least Squares

Sample(adjusted): 1958:4 2002:2

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.004830	0.000693	6.968648	0.0000
DLOG(YPDH)	0.403951	0.060521	6.674564	0.0000
DLOG(NETWORTHH)	0.056404	0.029640	1.902992	0.0587
D(FCM5(-1))	-0.004213	0.000972	-4.335417	0.0000
D(LR(-1))	-0.006736	0.001706	-3.949017	0.0001
R-squared	0.318649	Mean dependent var		0.008801
Adjusted R-squared	0.302617	S.D. dependent var		0.007035
S.E. of regression	0.005875	Sum squared resid		0.005868
F-statistic	21.99385	Durbin-Watson stat		2.389925
Prob(F-statistic)	0.000000			

### A1.2 Investment

#### A1.2.1 Nonresidential Investment

Dependent Variable: LOG(FNH)

Sample(adjusted): 1982:1 2002:2

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.811674	0.250503	3.240175	0.0018
YCP(-3)	0.000165	7.11E-05	2.320370	0.0230
AAA(-3)	-0.004795	0.002702	-1.774301	0.0800
LOG(FNH(-1))	0.872678	0.042475	20.54583	0.0000
AR(1)	0.438524	0.106601	4.113690	0.0001
R-squared	0.997075	Mean dependent var		6.607826
Adjusted R-squared	0.996923	S.D. dependent var		0.326219
S.E. of regression	0.018096	Sum squared resid		0.025215
F-statistic	6562.024	Durbin-Watson stat		2.136651
Prob(F-statistic)	0.000000			
Inverted AR Roots	.44			

#### A1.2.2 Residential Investment

Dependent Variable: DLOG(FRH)

Sample(adjusted): 1972:1 2002:2

Included observations: 122 after adjusting endpoints

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-0.006540	0.005330	-1.227097	0.2222
D(FCM(-1))	-0.055163	0.009118	-6.049674	0.0000

DLOG(YPDH)	1.364318	0.411827	3.312839	0.0012
AR(1)	0.213976	0.093415	2.290605	0.0238
R-squared	0.419156	Mean dependent var	0.004210	
Adjusted R-squared	0.404389	S.D. dependent var	0.048691	
S.E. of regression	0.037578	Sum squared resid	0.166628	
F-statistic	30.99012	Durbin-Watson stat	2.091786	
Prob(F-statistic)	0.000000			

### A1.2.3 Change in Private Inventory Stock

Dependent Variable: SH

Sample(adjusted): 1958:4 2002:2

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-8.538578	8.966702	-0.952254	0.3423
CH	-0.128005	0.016694	-7.667639	0.0000
GDPH	0.121091	0.009989	12.12231	0.0000
SH(-1)	0.797461	0.034040	23.42712	0.0000
AR(1)	0.890873	0.038131	23.36319	0.0000
R-squared	0.999880	Mean dependent var	874.0149	
Adjusted R-squared	0.999877	S.D. dependent var	313.9812	
S.E. of regression	3.486943	Sum squared resid	2066.991	
F-statistic	352630.3	Durbin-Watson stat	2.262544	
Prob(F-statistic)	0.000000			

## A1.3 Net Exports

### A1.3.1 Imports

Dependent Variable: LOG(MH)

Sample(adjusted): 1960:1 2002:2

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-1.029390	0.428868	-2.400250	0.0175
LOG(YPDH)	0.204454	0.084221	2.427595	0.0163
FCM5(-1)	-0.002287	0.001786	-1.280762	0.2021
LOG(JM)	-0.029393	0.017499	-1.679676	0.0949
LOG(MH(-1))	0.916323	0.037099	24.69927	0.0000
R-squared	0.997929	Mean dependent var	5.950851	
Adjusted R-squared	0.997879	S.D. dependent var	0.759995	
S.E. of regression	0.034999	Sum squared resid	0.202111	
F-statistic	19888.95	Durbin-Watson stat	2.029100	
Prob(F-statistic)	0.000000			

## A1.4 The Price Sector and The Phillips Curve

### A1.4.1 The Price Sector - JGDPB

Dependent Variable: D(JGDPB)

Sample(adjusted): 1958:4 2002:2

Variable	Coefficient	Std. Error	t-Statistic	Prob.
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C	-0.001855	0.025176	-0.073687	0.9413
D(JCZ)	0.590376	0.052228	11.30373	0.0000
D(JCZ(-1))	0.358981	0.050602	7.094254	0.0000
AR(1)	0.337836	0.073685	4.584874	0.0000
R-squared	0.876199	Mean dependent var	0.483543	
Adjusted R-squared	0.874027	S.D. dependent var	0.343964	
S.E. of regression	0.122082	Sum squared resid	2.548596	
F-statistic	402.2767	Durbin-Watson stat	2.116294	
Prob(F-statistic)	0.000000			



#### A1.4.2 The Price Sector – PCUSLFE

Dependent Variable: D(PCUSLFE)

Sample(adjusted): 1958:4 2002:2

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.184946	0.062980	2.936583	0.0038
D(JCZ)	0.945010	0.115027	8.215520	0.0000
D(JCZ(-1))	0.489434	0.108019	4.531005	0.0000
AR(1)	0.429206	0.071925	5.967386	0.0000
R-squared	0.802766	Mean dependent var		0.916571
Adjusted R-squared	0.799305	S.D. dependent var		0.589314
S.E. of regression	0.264006	Sum squared resid		11.91860
F-statistic	234.7825	Durbin-Watson stat		2.090226
Prob(F-statistic)	0.000000			

#### A1.4.3 The Phillips Curve

Dependent Variable: ROJCZ

Sample(adjusted): 1958:4 2002:2

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	1.578255	0.424668	3.716443	0.0003
ROJCZ(-1)	0.558297	0.106478	5.243295	0.0000
ROJCZ(-2)	-0.014093	0.087037	-0.161918	0.8716
ROJCZ(-3)	0.066999	0.075122	0.891875	0.3738
ROJCZ(-4)	-0.004830	0.079527	-0.060735	0.9516
ROJCZ(-5)	0.112262	0.076241	1.472466	0.1429
ROJCZ(-6)	0.209222	0.075739	2.762401	0.0064
ROJCZ(-7)	0.018230	0.076392	0.238642	0.8117
ROJCZ(-8)	-0.150658	0.076807	-1.961504	0.0516
ROJCZ(-9)	-0.026275	0.076060	-0.345453	0.7302
ROJCZ(-10)	0.189898	0.066009	2.876865	0.0046
NIXON	-1.480664	0.682180	-2.170491	0.0315
NIXOFF	0.157713	0.652238	0.241802	0.8092
LR	-0.200009	0.091138	-2.194569	0.0296
INFLDIFF	0.096735	0.011447	8.450442	0.0000
LXNFAROG	-0.080607	0.035518	-2.269459	0.0246
R-squared	0.884714	Mean dependent var		3.875444
Adjusted R-squared	0.873838	S.D. dependent var		2.695507
S.E. of regression	0.957423	Sum squared resid		145.7489
F-statistic	87.31266	Durbin-Watson stat		2.534212
Prob(F-statistic)	0.000000			

## A1.5 Okuns Law

Dependent Variable: LR

Sample(adjusted): 1958:4 2002:2

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.608752	0.333398	1.825900	0.0696
OUTPUTGAP(-1)	0.005059	0.003917	1.291449	0.1983
OUTPUTGAP(-2)	0.006139	0.003872	1.585447	0.1147
OUTPUTGAP(-3)	0.004505	0.003107	1.450024	0.1489
LR(-1)	0.896357	0.055640	16.11008	0.0000
AR(1)	0.613300	0.112590	5.447216	0.0000
R-squared	0.967452	Mean dependent var	5.919810	
Adjusted R-squared	0.966489	S.D. dependent var	1.478173	
S.E. of regression	0.270594	Sum squared resid	12.37441	
F-statistic	1004.735	Durbin-Watson stat	1.939202	
Prob(F-statistic)	0.000000			

## A1.6 The Term Structure and Federal Reserve Board Reaction Function

### A1.6.1 The Federal Reserve Board Reaction Function

Dependent Variable: FFED

Sample(adjusted): 1971:2 2002:2

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-13.05495	4.603777	-2.835704	0.0054
OUTPUTGAP1	13.41899	4.531712	2.961131	0.0037
ROGJGDPB	0.140388	0.047848	2.934060	0.0040
FFED(-1)	0.883448	0.048503	18.21426	0.0000
AR(1)	0.124370	0.104131	1.194356	0.2347
R-squared	0.900392	Mean dependent var	7.199600	
Adjusted R-squared	0.897071	S.D. dependent var	3.261108	
S.E. of regression	1.046245	Sum squared resid	131.3555	
F-statistic	271.2158	Durbin-Watson stat	1.928562	
Prob(F-statistic)	0.000000			

## A1.7 Income Sector

### A1.7.1 Personal Income

Dependent Variable: LOG(YP)

Sample(adjusted): 1958:4 2002:2

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-0.450090	0.021536	-20.89936	0.0000
LOG(GDP)	1.031340	0.002743	375.9544	0.0000
D(JCZ)	0.005727	0.003146	1.820668	0.0704
AR(1)	0.805805	0.043955	18.33271	0.0000
R-squared	0.999957	Mean dependent var	7.612828	

Adjusted R-squared	0.999956	S.D. dependent var	1.009191
S.E. of regression	0.006681	Sum squared resid	0.007634
F-statistic	1323147.	Durbin-Watson stat	1.990711
Prob(F-statistic)	0.000000		

### ***A1.7.2 Household Networth***

Dependent Variable: NETWORTH

Sample(adjusted): 1958:4 2002:2

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	22.35851	69.26047	0.322818	0.7472
NETWORTH(-1)	0.975371	0.023456	41.58335	0.0000
YPD	0.193589	0.127915	1.513422	0.1320
R-squared	0.998235	Mean dependent var	13593.24	
Adjusted R-squared	0.998214	S.D. dependent var	12279.27	
S.E. of regression	518.8913	Sum squared resid	46310692	
F-statistic	48636.55	Durbin-Watson stat	2.092402	
Prob(F-statistic)	0.000000			