Money Supply in United States Economy

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Math 4130

Abstract

The data that needed to be analyzed consisted of data for how large the M3 money supply was in the United States between 1959 and 1992. The money supply M3 consists of many types of money and this data was recorded on a monthly basis. Since the money supply was increasing over time the data needed to become stationary. To make the data stationary, first order differencing and second order differencing was used. Then the Box-Jenkins method was used to find an adequate model, which included autoregressive and moving average for multiple lags. The forecasting that was included with the adequate model was the most important part because it predicted that the money supply was going to continue to increase in the future. This is important because since the value of money always decreases as time moves forward, the money supply should always be increasing.

Introduction

The money supply, also called the money stock, consists of the total amount of monetary assets available in an economy at a specific time. There are groups of money supply and each consist of different types of money. The dataset consisted of data from the M3 money supply in the United States between the years of 1959-1992 on a monthly basis. The type of money that M3 consists of are notes and coins in circulation, traveler's checks of non-bank issuers, demand deposits, other checkable deposits, savings deposits, time deposits less than $100,000 and money-market deposit accounts for individuals, large time deposits, institutional money market funds, short-term repurchase and other liquid assets. This data is important because it provides us with an estimate of how much money is circulating around the US economy. With this information we can find an adequate model that can provide us with an accurate forecast of what the money supply is going to look like in the future. Since 2006, the US central bank no longer publishes amounts for M3, however there are various private institutions that produce estimates. Forecasts on the money supply are important to us because they help us understand how much inflation, the rate at which the general level of prices for goods and services is rising, and the depreciation of the dollar are correlated. As inflation increases, people will be required to use more money to buy the same products, therefore the value of the dollar depreciates and the amount of money needed in the economy increases.

Statistical Analysis

The statistical package that was used to analysis and find an adequate model for this data was SAS version 9.4. When first looking at the data you notice that it is not stationary because the first three quarters of the graph look like it follows an exponential trend, then the last part of the graph looks like it switches to a logarithmic trend (Figure 2.1 in appendix). To make the data stationary taking the log did not help because it barely adjusted anything. However, adding first order and seasonal differencing does make the data stationary. Adding first order and seasonal differencing worked because the plot of the observations now had a constant variation around the mean. Another way you can tell that the data became stationary was by noticing that the autocorrelations and partial autocorrelations lags died down quickly. Then using a factored ARIMA model along with autoregressive with additive factors 1, 2, 3, 7 and a moving average with additive factors 8, 10, 12, creates an adequate model (Figure 2.3 in appendix). You can figure out which lags to include for the autoregressive and moving average by including them one by one and trying different combinations to see which ones are significant. In the end the adequate model that best represented the original data is

ARIMA p=(1, 2, 3, 7) d=(1, 12) q=(8, 10, 12) NO INT (1.1)

Before I talk about why model 1.1 is the best model, I am going to talk about the other methods I tried, whether they produced an adequate model or not. Since seasonal differencing was successful in helping the data become stationary one could try using season dummies even though the data does not follow a season trend. All of the p-values for the dummies were way over 5% telling me that none of them are significant for this model and that using seasonal dummies is not the way to go. Looking at the original data you can notice that the graph starts out having an exponential trend and then towards the end the trend changes to a logarithmic trend. This could signal you to try to add an exponential and logarithmic trend to the model but neither of them were significant and it did not look like it helped the model at all. After trying a few more different methods it became clear that the Box-Jenkins methodology was going to work. That is when a factored ARIMA model was used to create adequate model 1.1.

After finding this adequate model I did not stop, I continued to find other adequate models that might be better than my first. Since the original data follows a linear trend, we can create another adequate model by adding a linear trend to model 1.1 and creating the following model

Linear Trend + ARIMA p=(1, 2, 3, 7) d=(1, 12) q=(8, 10, 12) NO INT (1.2)

Models 1.1 and 1.2 are very similar models and that is why their autocorrelations and partial autocorrelations and white noise charts look very similar. However, their forecasting models look very different and I will talk about this when I tell you why model 1.1 is the better model. Everything that was included in both models was significant because their p-values were well below 5% (Figure 2.6 in appendix). The root mean square error was also very similar between the two models, 5.20690 for model 1.1 and 5.17631 for model 1.2 (Figure 2.2 in appendix). Model 1.2 did have a slightly better confidence interval for the next 10 years because it was a little smaller than model 1.1's confidence interval. Even though both models passed the white noise test, both models had a few lags past 30 that were borderline and this could be because the data is very large and those few lags are false rejections, meaning they are giving me false information (Figure 2.5 in appendix).

The reason why model 1.1 is better than model 1.2 is because of the forecasting. According to model 1.1, the money supply will continue to follow the same pattern and increase (Figure 2.8 in appendix). This makes sense because the value of money is always depreciating and if the value of money always depreciates, the amount of money in the economy should be increasing. According to model 1.2, the forecasting showed that the money supply was going to increase the first few years and then decrease from there on out. This does not make sense because there is no evidence in the original data or in the US economy that the money supply would ever decrease. The money supply has been increasing ever since the central bank started measuring it, therefore model 1.2 may be adequate according to SAS but when you apply it to the real world you realize how model 1.2 gives false information.

The equation for model 1.1 is as follows:

$$z_t = y_t - y_{t-1} - y_{t-12} + y_{t-12-1} + \delta + \phi_1 z_{t-1} + \phi_2 z_{t-2} + \phi_3 z_{t-3} + \phi_7 z_{t-7} + a_t + \delta +$$

$$+a_t - \sigma_8 a_{t-8} - \sigma_{10} a_{t-10} - \sigma_{12} a_{t-12}$$

Conclusions

According to SAS, model 1.1 is an adequate model. The reason model 1.1 is an adequate model is because all of the included factors have a p-value less than 5% which means they are all significant and the model also passes the white noise test. Since model 1.1 is adequate, we can use that to predict how high the money supply will be in the United States. The model's forecasting shows us that the money supply will follow its previous trend and continue to increase over the next 10 years. This makes complete sense because ever since money was created it has been depreciating and it will always depreciate in the future. Since the value of money will always depreciate and the fact that there is always some form of inflation going on, the amount of money in the United States economy should increase. This is exactly what model 1.1's forecasting tells us, therefore we can conclude that this model is an accurate representation of the real world and can be used to predict the money supply in the future.

References

Bowerman, Bruce L., Richard T. O'Connell, and Anne B. Koehler. *Forecasting, Time Series, and Regression: An Applied Approach*. Belmont, CA: Thomson Brooks/Cole, 2005. Print.

"M3, U.S. 1959.1-1992.2." *DataMarket*. N.p., n.d. Web. 11 Dec. 2016.

Root. "M3." *Investopedia*. N.p., 28 Nov. 2013. Web. 11 Dec. 2016.

Appendix

Figure 2.1 Original Data

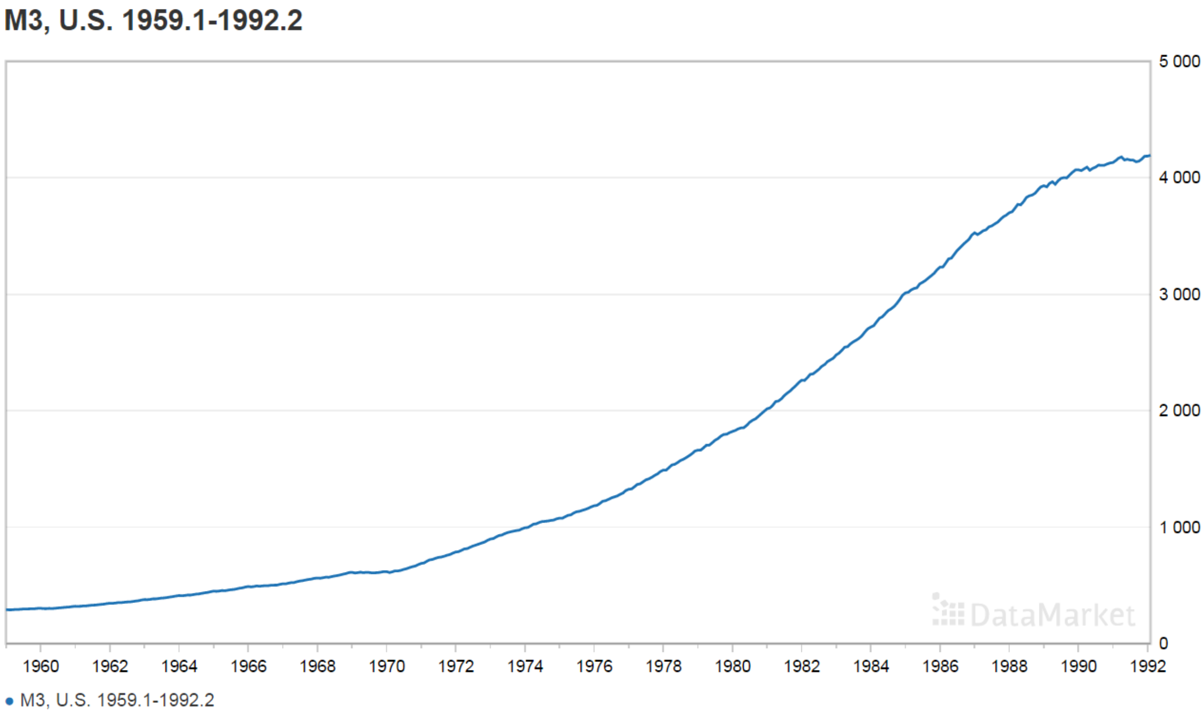

Figure 2.2

Statistics of Fit

Y: y

ARIMA p=(1, 2, 3, 7) d=(1, 12) q=(8, 10, 12) NOINT

Evaluation range: JAN1959 to FEB1992

Statistic of Fit	Value
Mean Square Error	27.11180
Root Mean Square Error	5.20690
Mean Absolute Percent Error	0.21986
Mean Absolute Error	3.57543
R-Square	1.000

Figure 2.3

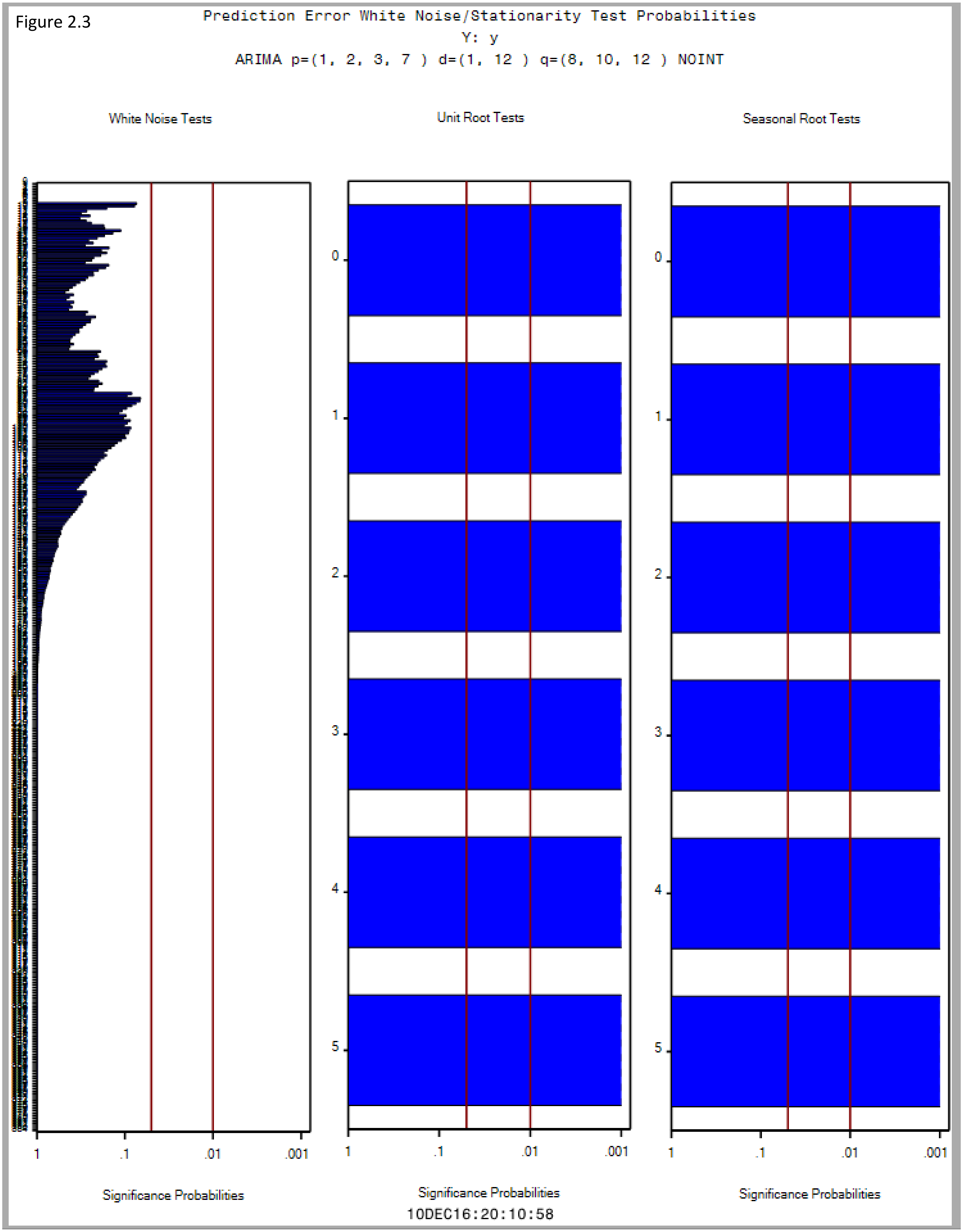
Prediction Error White Noise/Stationarity Test Probabilities
Y: y
ARIMA p=(1, 2, 3, 7) d=(1, 12) q=(8, 10, 12) NOINT
White Noise Tests
Unit Root Tests
Seasonal Root Tests
0
1
2
3
4
5
1
.1
.01
.001
Significance Probabilities
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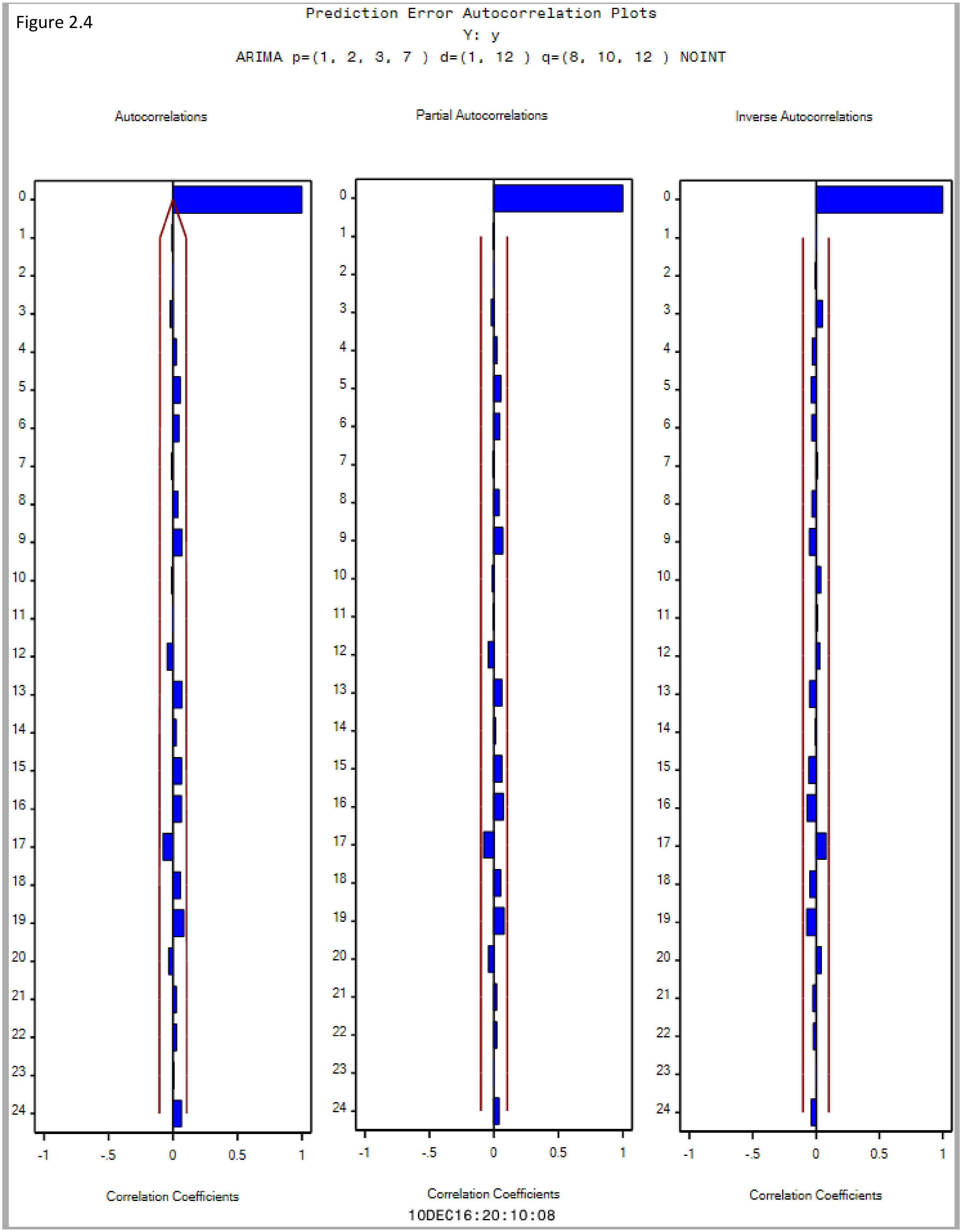
Figure 2.4



Prediction Error Autocorrelation Plots
Y: y
ARIMA p=(1, 2, 3, 7) d=(1, 12) q=(8, 10, 12) NOINT
Autocorrelations
Partial Autocorrelations
Inverse Autocorrelations
0
1
2
3
4
5
6
7
8
9
10
11
12
13
14
15
16
17
18
19
20
21
22
23
24
-1
-.5
0
0.5
1
Correlation Coefficients
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Figure 2.5

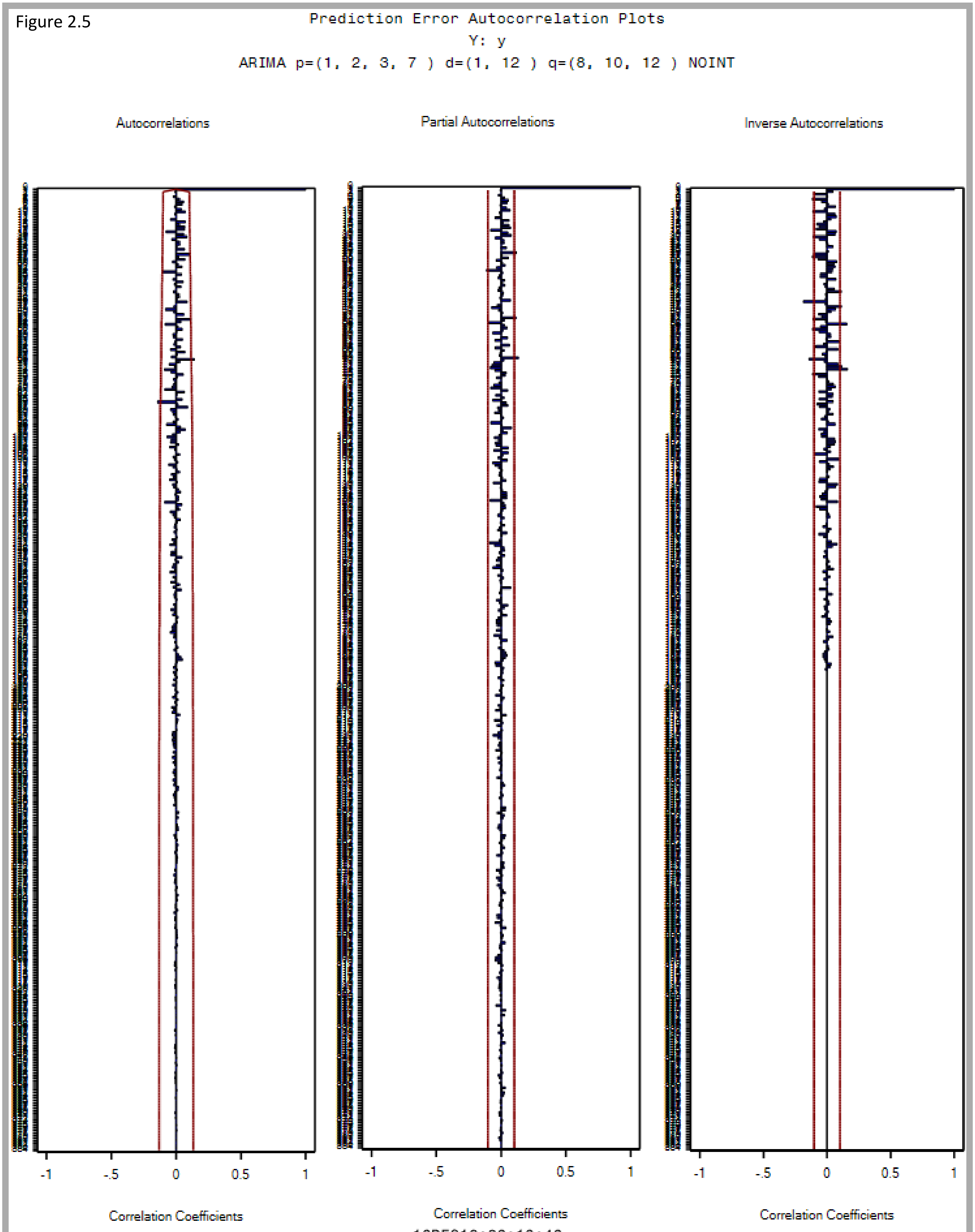
Prediction Error Autocorrelation Plots
Y: y
ARIMA p=(1, 2, 3, 7) d=(1, 12) q=(8, 10, 12) NOINT
Autocorrelations
Partial Autocorrelations
Inverse Autocorrelations
-1
-.5
0
0.5
1
Correlation Coefficients

Figure 2.6

Parameter Estimates
Y: y
ARIMA p=(1, 2, 3, 7) d=(1, 12) q=(8, 10, 12) NOINT
Fit range: JAN1959 to FEB1992

Model Parameter	Estimate	Std. Error	T	Prob>|T|
MA factor 1 lag 8	-0.20929	0.0432	-4.8410	<.0001
MA factor 1 lag 10	-0.17612	0.0425	-4.1472	<.0001
MA factor 1 lag 12	0.60565	0.0422	14.3637	<.0001
AR factor 1 lag 1	0.45993	0.0494	9.3070	<.0001
AR factor 1 lag 2	-0.16488	0.0539	-3.0567	0.0024
AR factor 1 lag 3	0.26005	0.0501	5.1882	<.0001
AR factor 1 lag 7	-0.14658	0.0502	-2.9225	0.0037
Model Variance (sigma squared)	27.60152	.	.	.

Figure 2.7 10-year prediction

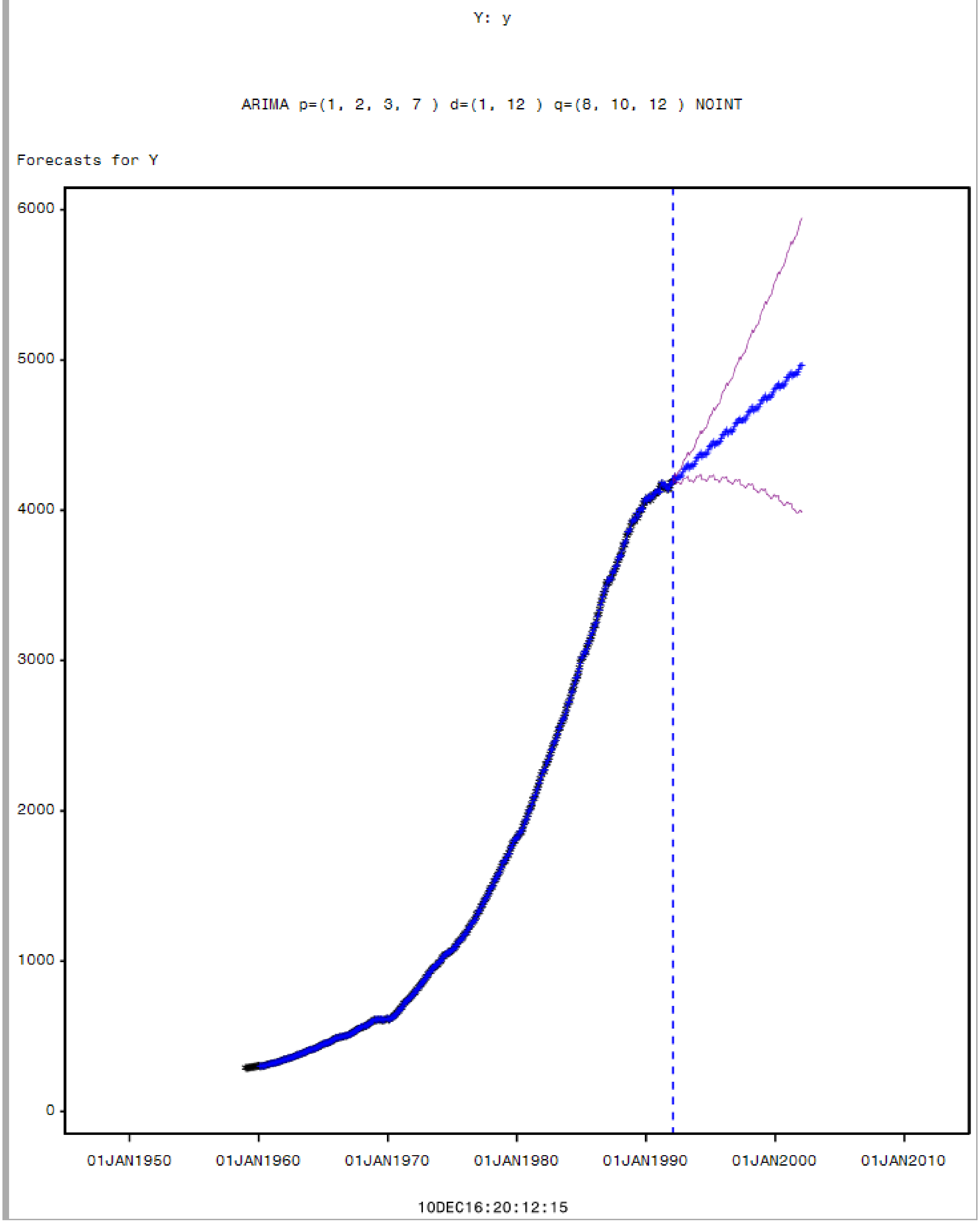

Figure 2.8 10-year prediction zoomed in

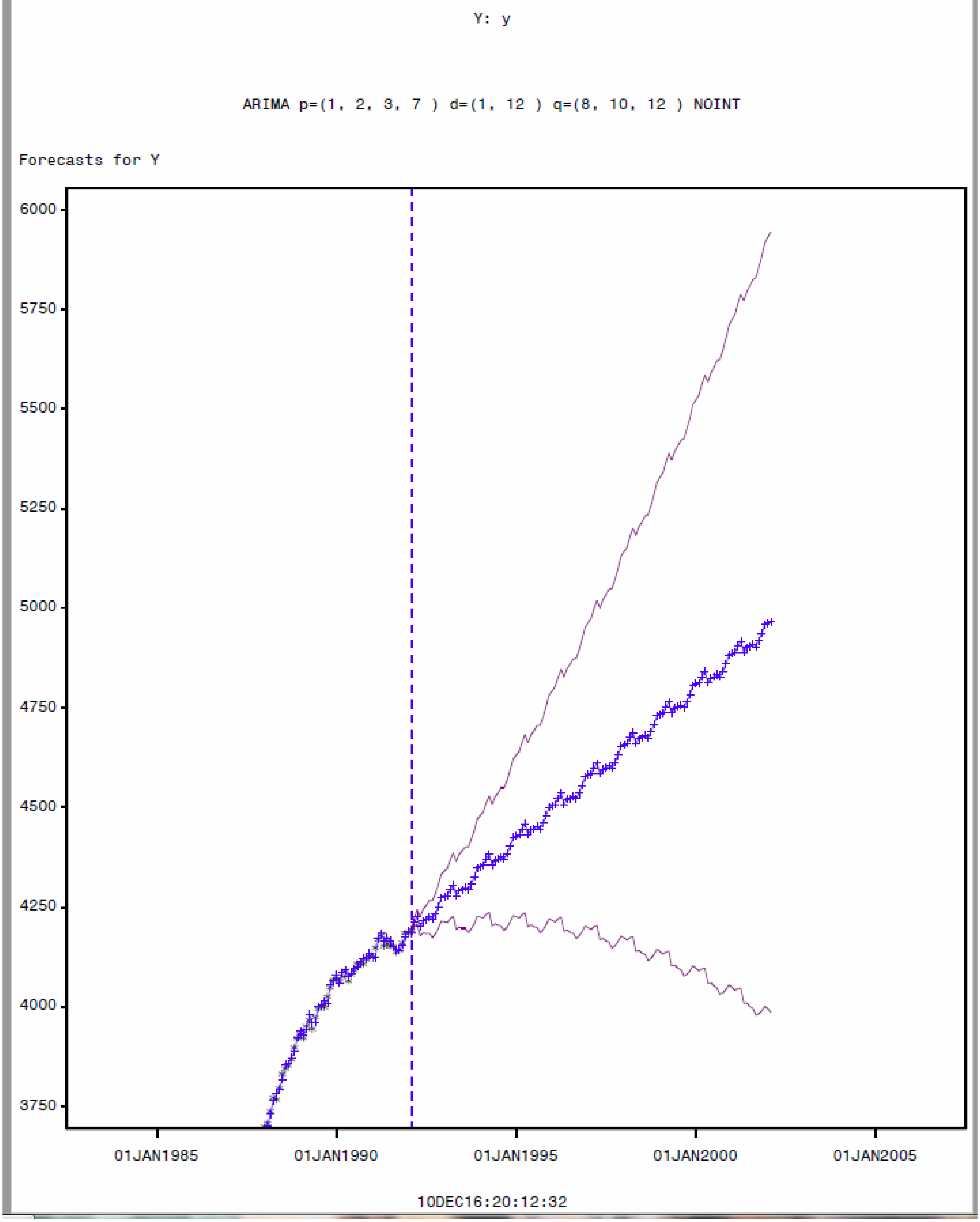

Figure 2.9

Y: y

ARIMA p=(1, 2, 3, 7) d=(1, 12) q=(8, 10, 12) NOINT

DATE	ACTUAL	PREDICT	U95	L95	ERROR	NERROR
01JAN1992	4186	4191	4201	4180	-4.9646	-0.9450
01FEB1992	4193	4184	4195	4174	8.5985	1.6366
01MAR1992	.	4212	4223	4202	.	.
01APR1992	.	4226	4245	4208	.	.
01MAY1992	.	4202	4226	4178	.	.
01JUN1992	.	4216	4246	4186	.	.
01JUL1992	.	4219	4255	4183	.	.
01AUG1992	.	4226	4267	4185	.	.
01SEP1992	.	4220	4266	4174	.	.
01OCT1992	.	4233	4284	4183	.	.
01NOV1992	.	4252	4307	4197	.	.
01DEC1992	.	4274	4333	4215	.	.
01JAN1993	.	4277	4341	4213	.	.
01FEB1993	.	4280	4348	4212	.	.
01MAR1993	.	4295	4368	4221	.	.
01APR1993	.	4307	4386	4227	.	.
01MAY1993	.	4279	4365	4194	.	.
01JUN1993	.	4291	4383	4200	.	.
01JUL1993	.	4294	4391	4197	.	.
01AUG1993	.	4300	4402	4197	.	.
01SEP1993	.	4294	4401	4186	.	.
01OCT1993	.	4308	4420	4196	.	.
01NOV1993	.	4327	4444	4210	.	.
01DEC1993	.	4349	4471	4227	.	.
01JAN1994	.	4353	4480	4225	.	.
01FEB1994	.	4356	4488	4223	.	.
01MAR1994	.	4371	4510	4232	.	.
01APR1994	.	4383	4529	4237	.	.
01MAY1994	.	4356	4509	4203	.	.
01JUN1994	.	4368	4527	4209	.	.
01JUL1994	.	4371	4537	4205	.	.
01AUG1994	.	4376	4549	4204	.	.
01SEP1994	.	4370	4549	4192	.	.
01OCT1994	.	4384	4568	4200	.	.
01NOV1994	.	4403	4593	4213	.	.
01DEC1994	.	4425	4622	4229	.	.
01JAN1995	.	4429	4632	4226	.	.
01FEB1995	.	4432	4641	4223	.	.
01MAR1995	.	4447	4663	4231	.	.
01APR1995	.	4459	4683	4236	.	.
01MAY1995	.	4432	4663	4201	.	.

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Figure 2.10

Y: y

ARIMA p=(1, 2, 3, 7) d=(1, 12) q=(8, 10, 12) NOINT

DATE	ACTUAL	PREDICT	U95	L95	ERROR	NERROR
01JUN1995	.	4444	4683	4206	.	.
01JUL1995	.	4447	4693	4201	.	.
01AUG1995	.	4453	4706	4199	.	.
01SEP1995	.	4446	4707	4186	.	.
01OCT1995	.	4460	4727	4193	.	.
01NOV1995	.	4479	4753	4205	.	.
01DEC1995	.	4501	4782	4221	.	.
01JAN1996	.	4505	4793	4217	.	.
01FEB1996	.	4508	4803	4213	.	.
01MAR1996	.	4523	4826	4220	.	.
01APR1996	.	4536	4847	4224	.	.
01MAY1996	.	4509	4828	4189	.	.
01JUN1996	.	4521	4848	4193	.	.
01JUL1996	.	4523	4859	4187	.	.
01AUG1996	.	4529	4873	4185	.	.
01SEP1996	.	4523	4874	4171	.	.
01OCT1996	.	4537	4896	4178	.	.
01NOV1996	.	4556	4922	4189	.	.
01DEC1996	.	4578	4952	4203	.	.
01JAN1997	.	4581	4964	4199	.	.
01FEB1997	.	4584	4975	4194	.	.
01MAR1997	.	4600	4999	4201	.	.
01APR1997	.	4612	5020	4204	.	.
01MAY1997	.	4585	5001	4168	.	.
01JUN1997	.	4597	5022	4172	.	.
01JUL1997	.	4600	5034	4165	.	.
01AUG1997	.	4605	5048	4162	.	.
01SEP1997	.	4599	5050	4148	.	.
01OCT1997	.	4613	5073	4153	.	.
01NOV1997	.	4632	5100	4164	.	.
01DEC1997	.	4654	5131	4178	.	.
01JAN1998	.	4658	5143	4173	.	.
01FEB1998	.	4661	5154	4167	.	.
01MAR1998	.	4676	5179	4173	.	.
01APR1998	.	4688	5201	4176	.	.
01MAY1998	.	4661	5183	4139	.	.
01JUN1998	.	4673	5205	4142	.	.
01JUL1998	.	4676	5217	4135	.	.
01AUG1998	.	4681	5231	4131	.	.
01SEP1998	.	4675	5235	4116	.	.
01OCT1998	.	4689	5257	4121	.	.

10DEC16:20:13:07

Figure 2.11

Y: y

ARIMA p=(1, 2, 3, 7) d=(1, 12) q=(8, 10, 12) NOINT

DATE	ACTUAL	PREDICT	U95	L95	ERROR	NERROR
01NOV1998	.	4708	5285	4131	.	.
01DEC1998	.	4730	5317	4144	.	.
01JAN1999	.	4734	5330	4139	.	.
01FEB1999	.	4737	5342	4132	.	.
01MAR1999	.	4752	5367	4138	.	.
01APR1999	.	4765	5389	4140	.	.
01MAY1999	.	4737	5372	4103	.	.
01JUN1999	.	4750	5394	4105	.	.
01JUL1999	.	4752	5407	4097	.	.
01AUG1999	.	4758	5422	4093	.	.
01SEP1999	.	4752	5426	4077	.	.
01OCT1999	.	4766	5450	4082	.	.
01NOV1999	.	4785	5478	4091	.	.
01DEC1999	.	4807	5510	4103	.	.
01JAN2000	.	4810	5524	4097	.	.
01FEB2000	.	4813	5536	4090	.	.
01MAR2000	.	4829	5562	4095	.	.
01APR2000	.	4841	5585	4097	.	.
01MAY2000	.	4814	5568	4059	.	.
01JUN2000	.	4826	5591	4061	.	.
01JUL2000	.	4828	5604	4053	.	.
01AUG2000	.	4834	5620	4048	.	.
01SEP2000	.	4828	5625	4031	.	.
01OCT2000	.	4842	5649	4035	.	.
01NOV2000	.	4861	5678	4044	.	.
01DEC2000	.	4883	5710	4056	.	.
01JAN2001	.	4887	5724	4049	.	.
01FEB2001	.	4890	5738	4042	.	.
01MAR2001	.	4905	5764	4046	.	.
01APR2001	.	4917	5787	4047	.	.
01MAY2001	.	4890	5771	4009	.	.
01JUN2001	.	4902	5795	4010	.	.
01JUL2001	.	4905	5808	4001	.	.
01AUG2001	.	4910	5825	3996	.	.
01SEP2001	.	4904	5830	3979	.	.
01OCT2001	.	4918	5854	3982	.	.
01NOV2001	.	4937	5884	3990	.	.
01DEC2001	.	4959	5917	4001	.	.
01JAN2002	.	4963	5932	3994	.	.
01FEB2002	.	4966	5946	3986	.	.

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