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1. OLS estimator for AR(1) is biased, but consistent.

Consider $X_{t+1} = \phi_1 X_t + \varepsilon_{t+1}$, $\varepsilon_{t+1} \sim N(0, \sigma^2)$

square loss $L = \sum_{t=1}^T (\hat{X}_t - X_t)^2$

$$= \sum_{t=1}^T (\hat{\phi}_1 X_{t-1} - X_t)^2$$

$$\frac{\partial L}{\partial \hat{\phi}_1} = 0 \Rightarrow \hat{\phi}_1 = \frac{\sum_{t=1}^T X_{t-1} X_t}{\sum_{t=1}^T X_{t-1}^2}$$

$$= \phi_1 + \sum_{t=1}^T \frac{X_{t-1}}{\sum_{t=1}^T X_{t-1}^2} \varepsilon_t$$

ε_t is independent on X_{t-1} , but

dependent on $\sum_{t=1}^T X_{t-1}^2$.

Thus, $E(\hat{\phi}_1) \neq \phi_1$, so it is biased.

If under the assumption that $|\phi_1| < 1$, which means AR(1) is stationary, by ergodic thm, OLS estimator is consistent.

$$2. \quad \Gamma_t = 0.01 + 0.1 \Gamma_{t-2} + \varepsilon_t, \quad \varepsilon_t \sim N(0, 0.02)$$

$$(a) \quad E(\Gamma_t) = 0.01 + 0.1 E(\Gamma_{t-2})$$

$$\Rightarrow 0.9 \mu = 0.01 \Rightarrow \mu = \frac{1}{90}$$

$$\text{Var}(\Gamma_t) = 0.01 \text{Var}(\Gamma_{t-2}) + \text{Var}(\varepsilon_t)$$

$$\Rightarrow 0.99 \text{Var}(\Gamma_t) = 0.02$$

$$\Rightarrow \text{Var}(\Gamma_t) = \frac{2}{99}$$

$$(b) \quad \rho_1 = \text{Cov}(\Gamma_t, \Gamma_{t-1})$$

$$= \text{Cov}(0.01 + 0.1 \Gamma_{t-2} + \varepsilon_t, \Gamma_{t-1})$$

$$= 0$$

$$= \rho_1$$

$$r_2 = \text{Cov}(r_t, r_{t-2})$$

$$= \text{Cov}(0.01 + 0.1 r_{t-2} + \varepsilon_t, r_{t-2})$$

$$= 0.1 \text{Cov}(r_{t-2}, r_{t-2}) = 0.1 \cdot \frac{2}{99}$$

$$\rho_2 = r_2 / r_0 = 0.1$$

$$^{(c)} E_{100}[r_{101}] = E_{100}[0.01 + 0.1 r_{99} + \varepsilon_{101}]$$

$$= 0.01 + 0.1 \times 0.02 = 0.012$$

$$\text{error} = r_{101} - E_{100}[r_{101}] = \varepsilon_{101}$$

$$\text{Std. deviation} = \sqrt{0.02} = 0.1414$$

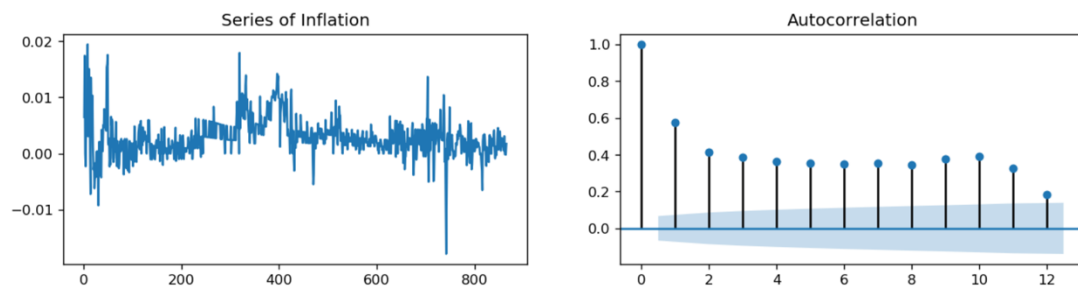
$$E_{100}[r_{102}] = E_{100}[0.01 + 0.1 r_{100} + \varepsilon_{102}]$$

$$= 0.01 + 0.1 \times 0.01 = 0.011$$

$$\text{error} = r_{102} - E_{100}[r_{102}] = \varepsilon_{102}$$

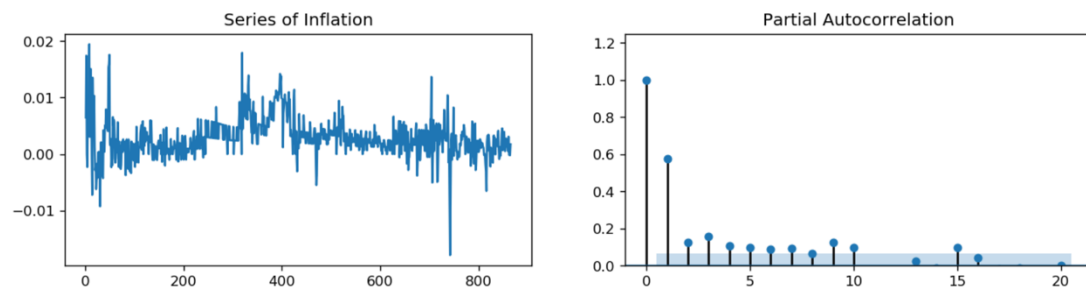
$$\text{Std deviation} = \sqrt{0.02} = 0.1414$$

3. (a)



(b)

Plot the PACF for the inflation series:



From the graph, we see that lag-1 is highly significant, so choose an AR(1) model.

AutoReg Model Results						
Dep. Variable:	pai		No. Observations:	865		
Model:	AutoReg(1)		Log Likelihood	3852.184		
Method:	Conditional MLE		S.D. of innovations	0.003		
Date:	Mon, 26 Apr 2021		AIC	-11.748		
Time:	20:43:25		BIC	-11.731		
Sample:	1		HQIC	-11.742		
	865					
	coef	std err	z	P> z	[0.025	0.975]
intercept	0.0012	0.000	9.723	0.000	0.001	0.001
pai.L1	0.5755	0.028	20.704	0.000	0.521	0.630
Roots						
	Real	Imaginary	Modulus	Frequency		
AR.1	1.7376	+0.0000j	1.7376	0.0000		

Using AIC:

AutoReg Model Results						
Dep. Variable:	pai		No. Observations:	865		
Model:	AutoReg(15)		Log Likelihood	3919.851		
Method:	Conditional MLE		S.D. of innovations	0.002		
Date:	Mon, 26 Apr 2021		AIC	-12.021		
Time:	20:43:42		BIC	-11.926		
Sample:	15		HQIC	-11.985		
	865					
	coef	std err	z	P> z	[0.025	0.975]
intercept	0.0004	0.000	3.191	0.001	0.000	0.001
pai.L1	0.4414	0.034	13.123	0.000	0.376	0.507
pai.L2	0.0763	0.036	2.098	0.036	0.005	0.148
pai.L3	0.0621	0.036	1.710	0.087	-0.009	0.133
pai.L4	0.0153	0.036	0.427	0.669	-0.055	0.085
pai.L5	0.0547	0.035	1.542	0.123	-0.015	0.124
pai.L6	0.0118	0.035	0.335	0.738	-0.057	0.081
pai.L7	0.0575	0.035	1.641	0.101	-0.011	0.126
pai.L8	0.0279	0.034	0.812	0.417	-0.039	0.095
pai.L9	0.0601	0.034	1.752	0.080	-0.007	0.127
pai.L10	0.0766	0.034	2.229	0.026	0.009	0.144
pai.L11	0.0702	0.034	2.039	0.041	0.003	0.138
pai.L12	-0.1683	0.034	-4.897	0.000	-0.236	-0.101
pai.L13	-0.0068	0.035	-0.197	0.844	-0.075	0.061
pai.L14	-0.0350	0.034	-1.025	0.305	-0.102	0.032
pai.L15	0.0948	0.031	3.010	0.003	0.033	0.156

Using BIC:

AutoReg Model Results

Dep. Variable:	pai	No. Observations:	865
Model:	AutoReg(12)	Log Likelihood	3907.258
Method:	Conditional MLE	S.D. of innovations	0.002
Date:	Mon, 26 Apr 2021	AIC	-11.966
Time:	20:55:49	BIC	-11.888
Sample:	12	HQIC	-11.936
	865		

	coef	std err	z	P> z	[0.025	0.975]
intercept	0.0005	0.000	3.771	0.000	0.000	0.001
pai.L1	0.4287	0.034	12.742	0.000	0.363	0.495
pai.L2	0.0509	0.036	1.396	0.163	-0.021	0.122
pai.L3	0.0472	0.036	1.301	0.193	-0.024	0.118
pai.L4	0.0596	0.036	1.658	0.097	-0.011	0.130
pai.L5	0.0507	0.035	1.438	0.150	-0.018	0.120
pai.L6	-0.0126	0.035	-0.358	0.720	-0.082	0.056
pai.L7	0.1013	0.035	2.878	0.004	0.032	0.170
pai.L8	0.0230	0.035	0.651	0.515	-0.046	0.092
pai.L9	0.0749	0.035	2.132	0.033	0.006	0.144
pai.L10	0.1126	0.035	3.227	0.001	0.044	0.181
pai.L11	0.0484	0.035	1.403	0.161	-0.019	0.116
pai.L12	-0.1759	0.032	-5.519	0.000	-0.238	-0.113

Python ar_select_order function selects AR(15) under AIC, and selects AR(12) under BIC.

4.

(a) Economically, the first difference is essentially the difference of current season earnings compared with the past season, while the seasonal difference is compared with the same season last year.

(b) The model is built in codes. The estimated model is:

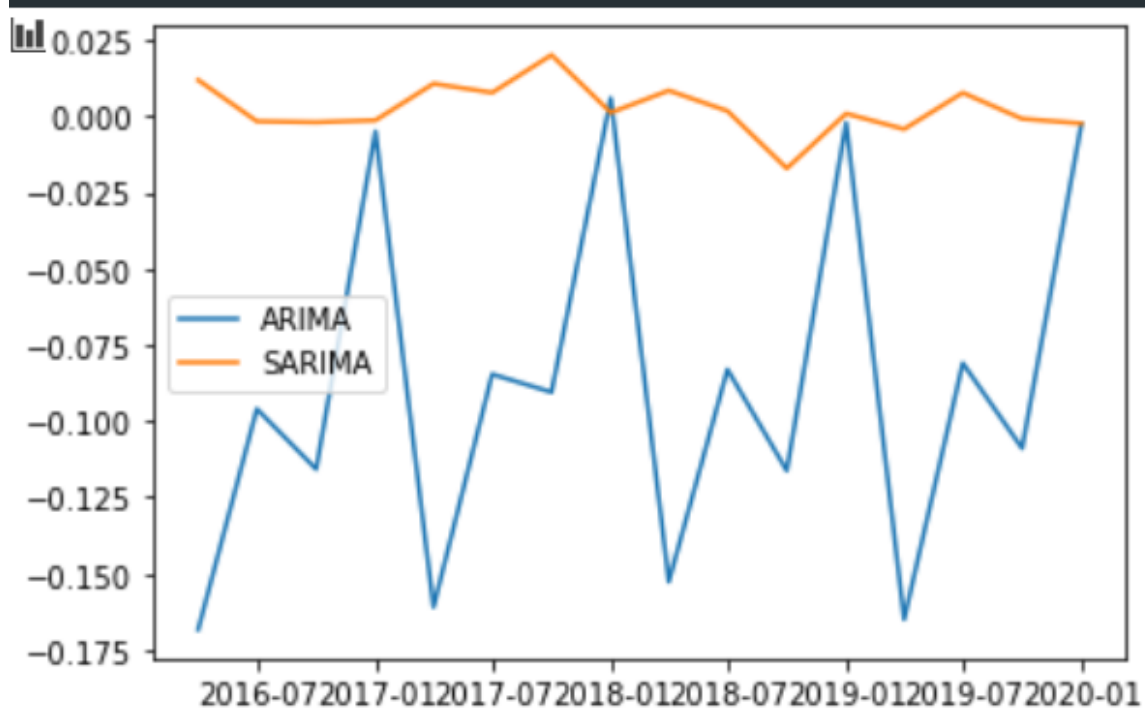
$$x_{t+1} - x_t = 0.0506 + \epsilon_{t+1} - 0.4920\epsilon_t$$

(c) The model is built in codes. The estimated model is:

$$(x_t - x_{t-1}) - (x_{t-4} - x_{t-5}) = (\epsilon_t - 0.1593\epsilon_{t-1}) - 0.4830(\epsilon_{t-4} - 0.1593\epsilon_{t-5})$$

In the model $\theta_1 = 0.1593$, $\theta_2 = 0.4830$, which means the past earning increase shocks (both the past season and the same season for the last year) is negatively correlated with predicted next season earnings.

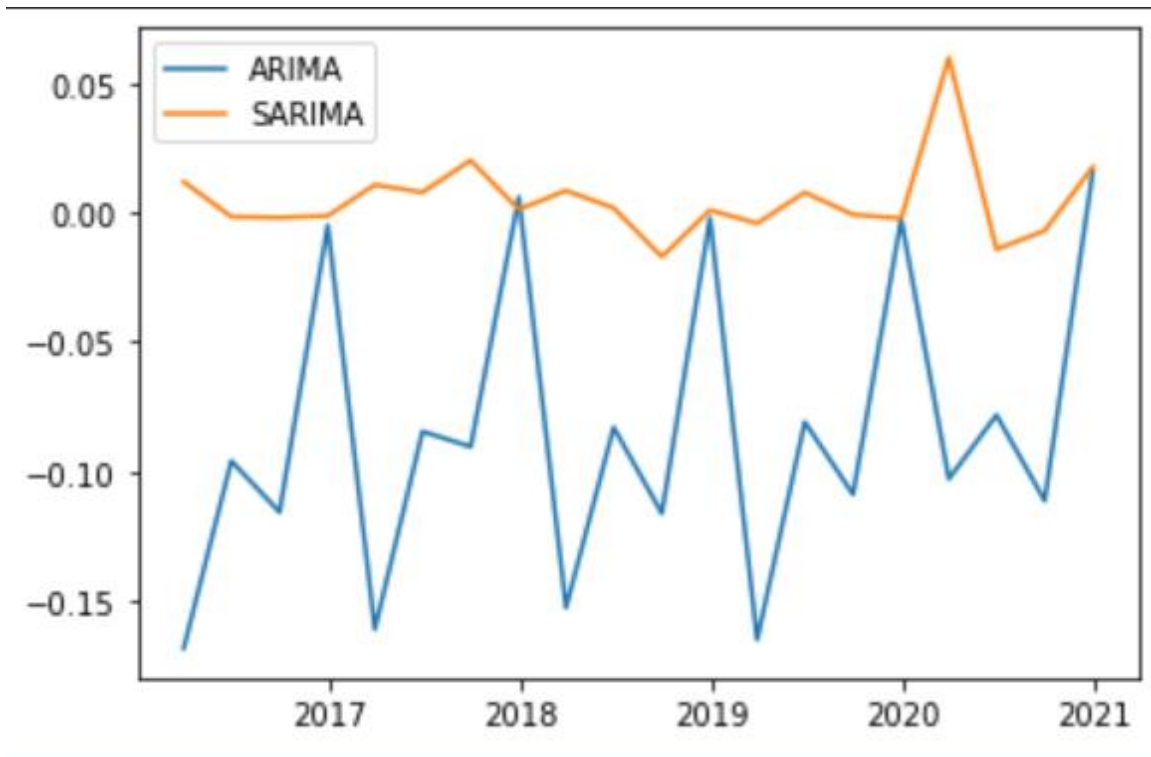
(d) (e)



ARIMA MSE: 0.01134832807889095
SARIMA MSE: 7.346810242072138e-05

The seasonal arima model (airline model) performs better.

(f)



Both models perform worse in 2020. This is because the COVID pandemic is an exogenous event outside of the description of the model. To improve the forecast accuracy, we might include macroeconomic predictors such as expected inflation, GDP growth, treasury rate, etc.