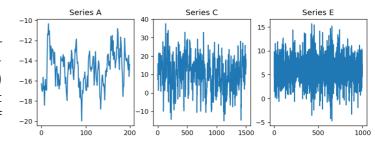
Code [will be] available @ https://github.com/szakrytnoy/financial-econometrics

#### 1 INTRODUCTION AND SCOPE

This assignment is dedicated to ARMA models - univariate class of econometric models, consisting of autoregressive AR(p) and stochastic MA(q) components. The moving average component represents a linear combination of q lags of white noise.



We are presented with 3 datasets: A, C and E. After graphical exploratory analysis, we assume weak stationarity of the series.

## 2 METHODOLOGY

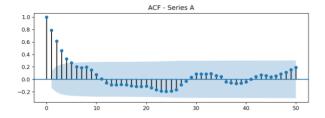
One of the common ways to determine optimal combinations of parameters (p, q) is to plot autocorrelation function (ACF) and partial autocorrelation function (PACF). The latter represents correlation coefficient between the original series and itself with lag = p and excludes the effects of lagged series in-between.

The criteria for optimal model is mirrored in cases of AR and MA processes:

- [AR] p spikes in PACF, geometrically decaying ACF
- [MA] q spikes in ACF, geometrically decaying PACF

Once the graphical analysis is done, we will evaluate one or more models with different parameters (p, q) and apply AIC criterion (the smaller - the better) to identify the optimal combination. The model will then be checked for autocorrelation of residuals, which by definition of autoregressive model should not be there.

### 3 SERIES A





AR(2) process is clearly visible from the charts with 2 spikes in PACF and decaying ACF. However, when running an automated script with values of p and q from 0 to 3, the one that generates minimal AIC is ARMA(1, 0). Trying to override this choice with ARMA(2, 0) results in an insignificant coefficient at the second lag.

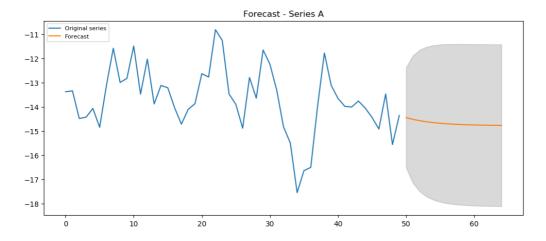
		ARMA	mode	I Kesu	112 		
Dep. Varia	ble:		 А	No. 0	bservations:		200
Model:		ARMA(1,	0)	Log L	ikelihood		-295.227
Method:		css-i	mle	S.D.	of innovatio	ns	1.056
Date:	Su	n, 06 Oct 20	019	AIC			596.454
Time:		17:10	:29	BIC			606.349
Sample:			0	HQIC			600.458
	coef	std err		z	P>   z	[0.025	0.975]
const	-14.7821	0.342	-43	. 258	0.000	-15.452	-14.112
ar.L1.A	0.7853	0.043	18	.167	0.000	0.701	0.870

Dep. Varia	ble:		A No	. Observation:	5:	200
Model:		ARMA(2,	<ol> <li>E</li> </ol>	g Likelihood		-295.227
Method:		css-	mle S.	D. of innovat:	ions	1.056
Date:	Su	n, 06 Oct 2	019 AI	C		598.454
Time:		17:11	:26 BI	C		611.647
Sample:			0 H	QIC		603.793
	coef	std err		z P> z	[0.025	0.975]
const	-14.7820	0.342	-43.25	8 0.000	-15.452	-14.112
ar.L1.A	0.7854	0.071	11.12	4 0.000	0.647	0.924
ar.L2.A	-0.0002	0.071	-0.00	92 0.998	-0.139	0.139

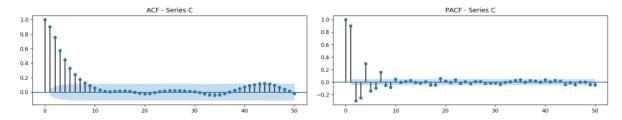
ARMA Model Results

Thus, decision has been made to stick to ARMA(1, 0). The Ljung-Box test shows no autocorrelation of residuals (pval = 0.58).

Last 50 observations and the forecasted values from ARMA(1, 0) with confidence intervals are presented below.



## 4 SERIES C

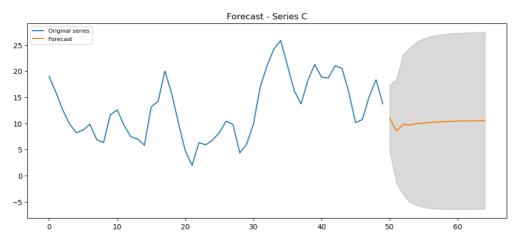


Similar to previous example, we see strong presence of PACF spikes that indicate AR process with geometrically decaying ACF. With 10 lags of significant PACF values at 5% confidence level, we will have to increase the maximal value of p when fitting semi-automated ARMA. Maximal values of p = 10 and q = 2 were chosen.

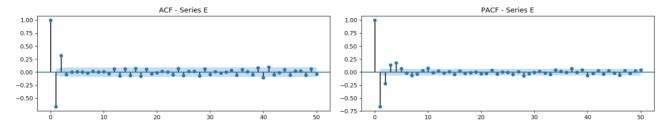
Unexpectedly, AIC criterion suggests going for ARMA(2, 2). Comparison against manual fit of ARMA(5, 0):

		ARMA	Model Resu	lts					ARMA M	odel Res	ults		
=========													
Dep. Variable	e:		C No. O	bservations:		1500	Dep. Variable:			C No.	Observations:		1500
Model:		ARMA(2,	2) Log L	ikelihood		-3888.369	Model:		ARMA(5, 0	) Log	Likelihood		-3918.940
Method:		css-m		of innovation	s	3.230	Method:		css-ml	e S.D.	of innovation	s	3.296
Date:	Si	un, 06 Oct 20				7788.738	Date:	Sur	n, 06 Oct 201	9 AIC			7851.879
Time:	3.	17:32:				7820.617	Time:		17:34:2	5 BIC			7889.072
Sample:		17.32.	0 HQIC			7800.614	Sample:			0 HQIC			7865.735
Sample:			e HÔIC			7800.014							
										======			
								coef	std err	z	P>   z	[0.025	0.975]
	coef	std err	z	P>   z	[0.025	0.975]							
							const	10.5764	0.656	16.131	0.000	9.291	11.862
const	10.5792	0.696	15.199	0.000	9.215	11.943	ar.L1.C	1.2055	0.026	47.123	0.000	1.155	1.256
ar.L1.C	0.4431	0.041	10.742	0.000	0.362	0.524	ar.L2.C	-0.0819	0.039	-2.122	0.034	-0.158	-0.006
ar.L2.C	0.2708	0.040	6.792	0.000	0.193	0.349	ar.L3.C	-0.5687	0.036	-15.902	0.000	-0.639	-0.499
ma.L1.C	0.7721	0.033	23.071	0.000	0.707	0.838	ar.L4.C	0.4523	0.039	11.697	0.000	0.377	0.528
ma.L2.C	0.6235	0.021	29.133	0.000	0.582	0.665	ar.L5.C	-0.1367	0.026	-5.338	0.000	-0.187	-0.087

In spite of all significant lags from 1 to 5, there is strong autocorrelation observed in the residuals, pval = 0.00. Therefore, once again we stick to the automated selection, where pval = 0.97 for the same test statistics. Forecast from the selected model ARMA(2, 2)



# 5 SERIES E



For the first time within this assignment, we are observing a situation with spikes on both ACF and PACF plots. The number of spikes indicate possible efficiency with a model ARMA(2, 3) or ARMA(3, 3). Maximal values of 5 are selected for both parameters for automated search.

Minimal AIC criterion renders suggestion for model ARMA(4, 5). However, the latter results in insignificant component of fourth AR lag. I then remove the insignificant lag and leave the model at ARMA(3, 5) and all significant coefficients:

		ARMA	Model Resu	ılts					ARMA	A Model Resu	lts		
Dep. Variable	e:		E No. 0	Observations:		1000	Dep. Variable			E No. O	bservations		1006
Model:		ARMA(4,	5) Log l	ikelihood		-2211.947	Model:		ARMA(3		ikelihood		-2214.264
Method:		css-	mle S.D.	of innovation	ıs	2.202	Method:				of innovatio	nns	2.209
Date:	Su	n, 06 Oct 2	019 AIC			4445.893	Date:	Su	n, 06 Oct :		J1 1111014411	,,,,	4448.52
Time:		18:19	:18 BIC			4499.878	Time:	54	18:20				4497.60
Sample:			0 HQIC			4466.411	Sample:		10.20	0 HQIC			4467.18
	coef	std err	z	P>   z	[0.025	0.975]		coef	std err	z	P>   z	[0.025	0.975
const	5.9930	0.015	391.903	0.000	5.963	6.023			0.054	447 227			6.07
ar.L1.E	-0.7036	0.061	-11.474	0.000	-0.824	-0.583	const	5.9794	0.051	117.227	0.000	5.879	6.079
ar.L2.E	0.5458	0.039	13.859	0.000	0.469	0.623	ar.L1.E	-1.8692	0.004	-519.471	0.000	-1.876	-1.86
ar.L3.E	1.0216	0.040	25.739	0.000	0.944	1.099	ar.L2.E	-1.8594	0.004	-485.738	0.000	-1.867	-1.85
ar.L4.E	0.1026	0.061	1.680	0.093	-0.017	0.222	ar.L3.E	-0.9901	0.000	-3065.576	0.000	-0.991	-0.98
ma.L1.E	-0.1028	0.054	-1.886	0.060	-0.210	0.004	ma.L1.E	1.0817	0.026	41.563	0.000	1.031	1.13
ma.L2.E	-0.5665	0.025	-22.287	0.000	-0.616	-0.517	ma.L2.E	0.9199	0.044	20.928	0.000	0.834	1.00
ma.L3.E	-0.2619	0.055	-4.801	0.000	-0.369	-0.155	ma.L3.E	0.4967	0.051	9.710	0.000	0.396	0.59
ma.L4.E	0.4178	0.039	10.748	0.000	0.342	0.494	ma.L4.E	0.1703	0.045	3.782	0.000	0.082	0.259
ma.L5.E	-0.4866	0.039	-12.370	0.000	-0.564	-0.410	ma.L5.E	0.5095	0.027	18.585	0.000	0.456	0.563

There is no autocorrelation present in the residuals, pval = 0.96. The final model is ARMA(3, 5).

