Econ 4858, Homework 2 - part 2, Professor Martins.

1. Use Kolmogorov's Law of Large Numbers to show that the method of moments estimators for $b$ that you obtained in question 4 of Homework 2 - part 1 is a consistent estimator.
Answer: By Kolmogorov's Law of Large Numbers $\bar{X} \xrightarrow{p} \frac{a+b}{2}$ and $s^{2} \xrightarrow{p} \frac{(b-a)^{2}}{12}$. Consequently, $s \xrightarrow{p} \frac{(b-a)}{2 \sqrt{3}}$. Hence,

$$
\hat{a}_{n}=\bar{X}-s \sqrt{3} \xrightarrow{p} \frac{a+b}{2}-\frac{(b-a)}{2 \sqrt{3}} \sqrt{3}=a
$$

and

$$
\hat{b}_{n}=\bar{X}+s \sqrt{3} \xrightarrow{p} \frac{a+b}{2}+\frac{(b-a)}{2 \sqrt{3}} \sqrt{3}=b
$$

2. Suppose $\left\{r_{t}\right\}_{t=1}^{n}$ is a random sample of log-returns on a certain financial asset and assume that $E\left(r_{t}\right)=$ $\mu$ and $V\left(r_{t}\right)=\sigma^{2}$. a) Using Lèvy's Central Limit Theorem obtain an asymptotically valid $\alpha=0.95$ confidence interval for $\mu$.
Answer: a) $\mu_{M M}=\frac{1}{n} \sum_{t=1}^{n} r_{t}$ and $E\left(\mu_{M M}\right)=\mu$ and $V\left(\mu_{M M}\right)=\sigma^{2} / n$.
By Lévy's CLT we have that

$$
\sqrt{n}\left(\frac{\mu_{M M}-\mu}{\sigma}\right) \xrightarrow{d} N(0,1) .
$$

Hence, for $\alpha=0.95$

$$
P\left(-1.96 \leq \sqrt{n} \frac{\mu_{M M}-\mu}{\sigma} \leq 1.96\right)=0.95
$$

which gives

$$
P\left(\mu_{M M}-1.96 \sigma / \sqrt{n} \leq \mu \leq \mu_{M M}+1.96 \sigma / \sqrt{n}\right)=0.95
$$

Substituting $\sigma$ with $\sqrt{\sigma_{M M}^{2}}$ provides the upper and lower bound for the interval.
3. Suppose that log-returns $\left\{r_{t}\right\}_{t=1,2, \ldots}$ on a financial asset follow an $\operatorname{AR}(1)$ process given by

$$
r_{t}=\alpha r_{t-1}+\varepsilon_{t}, \text { where } \varepsilon_{t} \sim N I D\left(0, \sigma^{2}\right)
$$

Obtain $E\left(r_{t}\right), V\left(r_{t}\right)$ and the autocovariance function of this process.
Answer: Under the assumption that $|\alpha|<1$, the process is covariance stationary. Hence, $E\left(r_{t}\right)=$ $E\left(r_{t-1}\right)=\mu$. Hence, since $E\left(\varepsilon_{t}\right)=0, \mu=\alpha \mu \Longleftrightarrow(1-\alpha) \mu=0$. Since $\alpha \neq 1, \mu=0$.
Again, by stationarity and the fact that $\mu=0, V\left(r_{t}\right)=E\left(r_{t}^{2}\right)=E\left(\alpha^{2} r_{t-1}^{2}+\varepsilon_{t}^{2}+2 \varepsilon_{t} r_{t-1}\right)=\alpha^{2} E\left(r_{t-1}^{2}\right)+$ $\sigma^{2}$. The last equality follows from the fact that $r_{t-1}$ and $\varepsilon_{t}$ are independent. Then, re-arranging the last equality $V\left(r_{t}\right)=\frac{\sigma^{2}}{1-\alpha^{2}}$. From your class notes, the fact that $\mu=0$, and repeated substitution of lagged values,

$$
\gamma(h)=\operatorname{Cov}\left(r_{t}, r_{t-1}\right)=E\left(r_{t}, r_{t-1}\right)=E\left(\sum_{j=0}^{\infty} \alpha^{j} \varepsilon_{t-j} \sum_{j=0}^{\infty} \alpha^{j} \varepsilon_{t-h-j}\right)=\frac{\sigma^{2} \alpha^{|h|}}{1-\alpha^{2}}
$$

for $h= \pm 1, \pm 2, \cdots$
4. Answer problems 1, 2 and 6 from chapter 4 of your textbook.

Answer: 1. (a) Yes, since $|-0.7|<1$. (b) $E\left(Y_{t}\right)=5-0.7 E\left(Y_{t-1}\right)$. By stationarity $E\left(Y_{t}\right)=E\left(Y_{t-1}\right)$, hence $E\left(Y_{t}\right)=5 / 1.7$. (c) $V\left(Y_{t}\right)=\frac{\sigma_{\epsilon}^{2}}{1-\alpha_{1}^{2}}=\frac{2}{1-0.49}$. (d) $\operatorname{Cov}\left(Y_{t}, Y_{t \pm h}\right)=\frac{\sigma_{\epsilon}^{2}}{1-\alpha_{1}^{2}} \alpha_{1}^{|h|}=\frac{2(-0.7)^{|h|}}{1-0.49}$.
2. (a) $V\left(Y_{t}\right)=\frac{2}{1-0.09}$. (b) $\operatorname{Cov}\left(Y_{1}, Y_{3}\right)=\frac{\sigma_{\epsilon}^{2}}{1-\phi^{2}} \phi^{2}=\frac{2}{1-0.09} 0.3^{2}$. (c) $V\left(\left(Y_{1}+Y_{3}\right) / 2\right)=V\left(Y_{1} / 2\right)+$ $V\left(Y_{3} / 2\right)+2 \operatorname{Cov}\left(Y_{1} / 2, Y_{3} / 2\right)=\frac{1}{2} \frac{\sigma_{\epsilon}^{2}}{1-\alpha_{1}^{2}}+\frac{1}{2} \operatorname{Cov}\left(Y_{1}, Y_{3}\right)=\frac{1}{2} \frac{\sigma_{\epsilon}^{2}}{1-\alpha_{1}^{2}}+\frac{1}{2} \frac{\sigma_{\epsilon}^{2}}{1-\phi^{2}} \phi^{2}$.
6. (a) Multiplying $Y_{t}-\mu$ by $Y_{t-k}-\mu$ we have

$$
\begin{equation*}
\left(Y_{t}-\mu\right)\left(Y_{t-k}-\mu\right)=\phi_{1}\left(Y_{t-k}-\mu\right)\left(Y_{t-1}-\mu\right)+\phi_{2}\left(Y_{t-k}-\mu\right)\left(Y_{t-2}-\mu\right)+\left(Y_{t-k}-\mu\right) \epsilon_{t} \tag{1}
\end{equation*}
$$

Taking expectations on both sides gives $\gamma(k)=\phi_{1} \gamma(k-1)+\phi_{2} \gamma(k-2)$. Dividing this last equation by $\gamma(0)$ we have

$$
\begin{equation*}
\rho(k)=\phi_{1} \rho(k-1)+\phi_{2} \rho(k-2) . \tag{2}
\end{equation*}
$$

(b) Now, evaluating (2) at $k=1,2$ and noting that $\rho(0)=1$ we have

$$
\rho(1)=\phi_{1}+\phi_{2} \rho(1) \text { and } \rho(2)=\phi_{1} \rho(1)+\phi_{2} .
$$

Writing these two equations in matrix format completes the proof.
(c) Substituting the given values of $\rho(1)$ and $\rho(2)$ we have $\phi_{1}=0.38$ and $\phi_{2}=0.0476$. Now, $\rho(3)=$ $0.38 \times 0.2+0.0476 \times 0.4$.
5. Suppose that the log-returns on a financial asset are generated by an $\operatorname{AR}(1)$ process given by

$$
\begin{equation*}
r_{t}=\alpha r_{t-1}+\varepsilon_{t}, \text { where } \varepsilon_{t} \sim N I D\left(0, \sigma^{2}\right) \tag{3}
\end{equation*}
$$

with $|\alpha|<1$.
(a) Given a sample $\left\{r_{t}\right\}_{t=1}^{n}$ of size $n$, derive the least squares estimator for $\alpha$.

Answer: The least squares estimator for $\alpha$ is given by

$$
\hat{\alpha}=\operatorname{argmin}_{\alpha} S_{n}(\alpha)=\operatorname{argmin}_{\alpha} \sum_{t=2}^{n}\left(r_{t}-\alpha r_{t-1}\right)^{2}
$$

Taking the derivative of $S_{n}(\alpha)$ with respect to $\alpha$ and setting it equal to zero gives,

$$
2 \sum_{t=2}^{n}\left(r_{t}-\hat{\alpha} r_{t-1}\right)\left(-r_{t-1}\right)=0
$$

which imples $\hat{\alpha}=\left(\sum_{t=2}^{n} r_{t-1}^{2}\right)^{-1} \sum_{t=2}^{n} r_{t-1} r_{t}$.
(b) Obtain the expected value and the variance of the estimator you derived in item a).

Answer: Obtained in class. $E(\hat{\alpha})=\alpha$ and $V\left(\hat{\alpha} \mid r_{1}, \cdots, r_{n-1}\right)=\sigma^{2} \frac{1}{\sum_{t=2}^{n} r_{t-1}^{2}}$. Also, $V(\hat{\alpha})=$ $\sigma^{2} E\left(\frac{1}{\sum_{t=2}^{n} r_{t-1}^{2}}\right)$
(c) Is the method of moments estimator for $\alpha$ the same as the least squares estimator for $\alpha$ ? Prove. Did you have to use normality in your proof?

Answer: Yes. Note that $r_{t} r_{t-1}=\alpha r_{t-1}^{2}+r_{t-1} \varepsilon_{t}$ and

$$
E\left(r_{t} r_{t-1}\right)=\alpha E\left(r_{t-1}^{2}\right)+E\left(r_{t-1} \varepsilon_{t}\right)
$$

Since, $E\left(r_{t-1} \varepsilon_{t}\right)=E\left(E\left(r_{t-1} \varepsilon_{t} \mid r_{t-1}\right)\right)=0$ we have

$$
\alpha=\frac{E\left(r_{t} r_{t-1}\right)}{E\left(r_{t-1}^{2}\right)}
$$

Hence, the method of moments estimator for $\alpha$ is

$$
\alpha_{M M}=\frac{\frac{1}{n} \sum_{t=2}^{n} r_{t-1} r_{t}}{\frac{1}{n} \sum_{t=2}^{n} r_{t-1}^{2}}
$$

and $\hat{\alpha}=\alpha_{M M}$. No normality is used.

