

LAWS OF LARGE NUMBERS FOR THE MAXIMAL ORDER STATISTICS FROM A TRIANGULAR ARRAY

BY

ANDRÉ ADLER

Abstract. Let $\{X_{nj}, 1 \leq j \leq n, n \geq 1\}$ be independent and identically distributed random variables with common density $f(x) = px^{-p-1}I(x \geq 1)$, where $p > 0$. Let X_{nk} be the k^{th} largest order statistic from $\{X_{n1}, \dots, X_{nn}\}$. We consider various laws of large numbers of the form

$$\frac{\sum_{n=k}^N a_n X_{nk}}{b_N} \rightarrow L$$

for some finite nonzero constant L . It turns out that Strong Laws exist when $pk \geq 1$, while not even a Weak Law exists when $pk < 1$.

1. Introduction. Let $\{X_{nj}, 1 \leq j \leq n, n \geq 1\}$ be independent and identically distributed random variables with density $f(x) = px^{-p-1}I(x \geq 1)$, where $p > 0$. Let X_{nk} be the k^{th} largest order statistic from each row of this triangular array. Therefore the density of X_{nk} is

$$f_{nk}(x) = \frac{p \cdot n!}{(n-k)!(k-1)!} (1-x^{-p})^{n-k} x^{-pk-1} I(x \geq 1).$$

Received by the editors March 9, 2001 and in revised form September 12, 2001.

AMS 2000 Subject Classification: 60F15, 60F05.

Key words and phrases: Laws of large numbers, order statistics, almost sure convergence, convergence in probability, slow variation.

In this paper we examine when Strong Laws and Weak Laws of the form

$$(1) \quad \frac{\sum_{n=k}^N a_n X_{nk}}{b_N} \rightarrow L$$

exist for constants a_n , b_N and L . Our goal is not only to find nonzero limits, L , but to show when these laws of large numbers do and do not exist.

2. Preliminaries. We need a couple of lemmas before we proceed.

From page 29 of Riordan [5] we have

Lemma 1.

$$\sum_{j=0}^n \frac{\binom{n}{j} (-1)^j}{j+m} = \frac{n!}{m(m+1)\cdots(m+n)} = \frac{\Gamma(m)n!}{\Gamma(n+m+1)}$$

and from page 257 of Abramowitz and Stegun [1] we have

Lemma 2.

$$\frac{\Gamma(n+a)}{\Gamma(n+b)} \sim n^{a-b} \quad \text{as } n \rightarrow \infty.$$

As usual we set $\lg x = \max\{1, \log x\}$ and we use C to denote a generic constant which need not be the same in each appearance. Also, we let $L(x)$ denote any slowly varying function. For more literature on slowly varying function see Seneta [6].

3. pk greater than one. It is important to note that even though pk exceeds one, we may have $p \leq 1$. Thus our original random variables may not possess a first moment. Hence we can use our second and third largest order statistics to achieve our limit results.

Theorem 1. *If $pk > 1$ and $\alpha > -1 - 1/p$, then*

$$\lim_{N \rightarrow \infty} \frac{\sum_{n=k}^N n^\alpha L(n) X_{nk}}{N^{\alpha+1+1/p} L(N)} = \frac{\Gamma(k-1/p)}{(\alpha+1+1/p)(k-1)!} \quad \text{almost surely}$$

for all slowly varying functions $L(n)$.

Proof. In this case we set $a_n = n^\alpha L(n)$, $b_n = n^{\alpha+1+1/p} L(n)$ and $c_n = b_n/a_n = n^{1+1/p}$ and we partition the series $b_N^{-1} \sum_{n=k}^N a_n X_{nk}$ into the following three terms:

$$\begin{aligned} b_N^{-1} \sum_{n=k}^N a_n X_{nk} &= b_N^{-1} \sum_{n=k}^N a_n [X_{nk} I(X_{nk} \leq c_n) - EX_{nk} I(X_{nk} \leq c_n)] \\ &\quad + b_N^{-1} \sum_{n=k}^N a_n X_{nk} I(X_{nk} > c_n) \\ &\quad + b_N^{-1} \sum_{n=k}^N a_n EX_{nk} I(X_{nk} \leq c_n). \end{aligned}$$

The second term vanishes almost surely since $pk > 1$ and

$$\begin{aligned} \sum_{n=k}^{\infty} P\{X_{nk} > c_n\} &= \sum_{n=k}^{\infty} \frac{p \cdot n!}{(n-k)!(k-1)!} \int_{c_n}^{\infty} (1-x^{-p})^{n-k} x^{-pk-1} dx \\ &< C \sum_{n=k}^{\infty} \frac{n!}{(n-k)!} \int_{c_n}^{\infty} x^{-pk-1} dx < C \sum_{n=k}^N \frac{n^k}{c_n^{pk}} \\ &= C \sum_{n=k}^{\infty} \left(\frac{n}{c_n^p}\right)^k = C \sum_{n=k}^{\infty} \left(\frac{n}{n^{1+p}}\right)^k = C \sum_{n=k}^{\infty} \frac{1}{n^{pk}} < \infty. \end{aligned}$$

As for the first term we use the usual Khintchine-Kolmogorov Convergence Theorem and Kronecker's lemma argument, see Chow and Teicher [3]. We examine three different possibilities. The first one is $1 < pk < 2$. In this case

$$\sum_{n=k}^{\infty} c_n^{-2} EX_{nk}^2 I(X_{nk} \leq c_n)$$

$$\begin{aligned}
&= \sum_{n=k}^{\infty} \frac{p \cdot n!}{c_n^2 (n-k)!(k-1)!} \int_1^{c_n} (1-x^{-p})^{n-k} x^{-pk+1} dx \\
&< C \sum_{n=k}^{\infty} \frac{n^k}{c_n^2} \int_1^{c_n} x^{-pk+1} dx < C \sum_{n=k}^{\infty} \frac{n^k}{c_n^2} c_n^{-pk+2} = C \sum_{n=k}^{\infty} \frac{n^k}{c_n^{pk}} < \infty
\end{aligned}$$

as in the previous calculation. If $pk = 2$, then

$$\begin{aligned}
\sum_{n=k}^{\infty} c_n^{-2} EX_{nk}^2 I(X_{nk} \leq c_n) &< C \sum_{n=k}^{\infty} \frac{n^k}{c_n^2} \int_1^{c_n} x^{-1} dx = C \sum_{n=k}^{\infty} \frac{n^k}{c_n^2} \lg c_n \\
&< C \sum_{n=k}^{\infty} \frac{n^k \lg n}{n^{2+2/p}} = C \sum_{n=k}^{\infty} \frac{\lg n}{n^2} < \infty.
\end{aligned}$$

Lastly, if $pk > 2$, then

$$\begin{aligned}
&\sum_{n=k}^{\infty} c_n^{-2} EX_{nk}^2 (X_{nk} \leq c_n) \\
&= \sum_{n=k}^{\infty} \frac{p \cdot n!}{c_n^2 (n-k)!(k-1)!} \int_1^{c_n} (1-x^{-p})^{n-k} x^{-pk+1} dx \\
&= \sum_{n=k}^{\infty} \frac{p \cdot n!}{c_n^2 (n-k)!(k-1)!} \sum_{j=0}^{n-k} \binom{n-k}{j} (-1)^{-j} \int_1^{c_n} x^{-p(j+k)+1} dx \\
&= \sum_{n=k}^{\infty} \frac{p \cdot n!}{c_n^2 (n-k)!(k-1)!} \sum_{j=0}^{n-k} \frac{\binom{n-k}{j} (-1)^j}{p(j+k)-2} \\
&\quad + \sum_{n=k}^{\infty} \frac{p \cdot n!}{c_n^2 (n-k)!(k-1)!} \sum_{j=0}^{n-k} \frac{\binom{n-k}{j} (-1)^{j+1} c_n^{-p(j+k)+2}}{p(j+k)-2}.
\end{aligned}$$

Next we use Lemmas 1 and 2, with $m = k - 2/p$. The first term is

$$\begin{aligned}
&\sum_{n=k}^{\infty} \frac{n!}{c_n^2 (n-k)!(k-1)!} \sum_{j=0}^{n-k} \frac{\binom{n-k}{j} (-1)^j}{j+m} \\
&= \sum_{n=k}^{\infty} \left(\frac{n!}{c_n^2 (n-k)!(k-1)!} \right) \left(\frac{(n-k)! \Gamma(m)}{\Gamma(n-k+m+1)} \right) \\
&< C \sum_{n=k}^{\infty} \frac{\Gamma(n+1)}{c_n^2 \Gamma(n-k+m+1)} < C \sum_{n=k}^{\infty} \frac{n^{-m+k}}{c_n^2}
\end{aligned}$$

$$= C \sum_{n=k}^{\infty} \frac{n^{2/p}}{n^{2+2/p}} = C \sum_{n=k}^{\infty} \frac{1}{n^2} < \infty.$$

As for the second term we have

$$\begin{aligned} & \left| \sum_{n=k}^{\infty} \frac{p \cdot n!}{c_n^2 (n-k)! (k-1)!} \sum_{j=0}^{n-k} \frac{\binom{n-k}{j} (-1)^{j+1} c_n^{-p(j+k)+2}}{p(j+k)-2} \right| \\ & < C \sum_{n=k}^{\infty} n^k \sum_{j=0}^{n-k} \binom{n-k}{j} c_n^{-p(j+k)} = C \sum_{n=k}^{\infty} \frac{n^k}{c_n^{pk}} \sum_{j=0}^{n-k} \binom{n-k}{j} [c_n^{-p}]^j \\ & = C \sum_{n=k}^{\infty} \left(\frac{n^k}{c_n^{pk}} \right) \cdot \left(1 + \frac{1}{c_n^p} \right)^{n-k} < C \sum_{n=k}^{\infty} \frac{1}{n^{pk}} < \infty \end{aligned}$$

since $pk > 2$.

Finally, we will examine the last term in our partition

$$\begin{aligned} EX_{nk} I(X_{nk} \leq c_n) &= \frac{p \cdot n!}{(n-k)! (k-1)!} \int_1^{c_n} (1-x^{-p})^{n-k} x^{-pk} dx \\ &= \frac{p \cdot n!}{(n-k)! (k-1)!} \sum_{j=0}^{n-k} \binom{n-k}{j} (-1)^j \int_1^{c_n} x^{-p(j+k)} dx \\ &= \frac{p \cdot n!}{(n-k)! (k-1)!} \sum_{j=0}^{n-k} \frac{\binom{n-k}{j} (-1)^j}{p(j+k)-1} \\ &\quad + \frac{p \cdot n!}{(n-k)! (k-1)!} \sum_{j=0}^{n-k} \frac{\binom{n-k}{j} (-1)^{j+1} c_n^{-p(j+k)+1}}{p(j+k)-1}. \end{aligned}$$

Using both our lemmas, with $m = k - 1/p$, the first term equals

$$\begin{aligned} & \frac{n!}{(n-k)! (k-1)!} \sum_{j=0}^{n-k} \frac{\binom{n-k}{j} (-1)^j}{j+m} \\ &= \left(\frac{n!}{(n-k)! (k-1)!} \right) \left(\frac{(n-k)! \Gamma(m)}{\Gamma(n-k+m+1)} \right) \\ &= \frac{\Gamma(k-1/p) \Gamma(n+1)}{(k-1)! \Gamma(n+1-1/p)} \sim \frac{\Gamma(k-1/p)}{(k-1)!} \cdot n^{1/p}. \end{aligned}$$

The other term in our first moment is bounded above by

$$\begin{aligned}
& \left| \frac{p \cdot n!}{(n-k)!(k-1)!} \sum_{j=0}^{n-k} \frac{\binom{n-k}{j} (-1)^{j+1} c_n^{-p(j+k)+1}}{p(j+k)-1} \right| \\
& < C n^k \sum_{j=0}^{n-k} \binom{n-k}{j} c_n^{-p(j+k)+1} = C n^k c_n^{-pk+1} \sum_{j=0}^{n-k} \binom{n-k}{j} c_n^{-pj} \\
& = C n^{-pk+1+1/p} \left(1 + \frac{1}{c_n^p}\right)^{n-k} < C n^{-pk+1+1/p} \left(1 + \frac{1}{c_n^p}\right)^{c_n^p} \\
& < C n^{-pk+1+1/p} = o(n^{1/p})
\end{aligned}$$

since $pk > 1$, thereby establishing

$$EX_{nk} I(X_{nk} \leq c_n) \sim \frac{\Gamma(k-1/p)}{(k-1)!} \cdot n^{1/p}.$$

This, together with $a_n = n^\alpha L(n)$ and $b_n = n^{\alpha+1+1/p} L(n)$ it follows, with probability one, that

$$\begin{aligned}
& \frac{\sum_{n=k}^N n^\alpha L(n) X_{nk}}{N^{\alpha+1+1/p} L(N)} \sim \frac{\sum_{n=k}^N a_n EX_{nk} I(X_{nk} \leq c_n)}{b_N} \\
& \sim \left(\frac{\Gamma(k-1/p)}{(k-1)!} \right) \cdot \left(\frac{\sum_{n=k}^N n^{\alpha+1/p} L(n)}{N^{\alpha+1+1/p} L(N)} \right) \rightarrow \frac{\Gamma(k-1/p)}{(\alpha+1+1/p)(k-1)!}
\end{aligned}$$

by using Theorem 1 from page 281 of Feller [4].

Next we reexamine our last result when $\alpha = -1 - 1/p$. Once again we obtain a Strong Law.

Theorem 2. *If $pk > 1$ and $a > -1$, then*

$$\lim_{N \rightarrow \infty} \frac{\sum_{n=k}^N n^{-1-1/p} (\lg n)^a X_{nk}}{(\lg N)^{a+1}} = \frac{\Gamma(k-1/p)}{(a+1)(k-1)!} \quad \text{almost surely.}$$

Proof. Here we set $a_n = n^{-1-1/p} (\lg n)^a$, $b_n = (\lg n)^{a+1}$ and $c_n = b_n/a_n = n^{1+1/p} \lg n$. As in the last proof we partition the series $b_N^{-1} \sum_{n=k}^N a_n X_{nk}$ into

the following three terms:

$$\begin{aligned} b_N^{-1} \sum_{n=k}^N a_n X_{nk} &= b_N^{-1} \sum_{n=k}^N a_n [X_{nk} I(X_{nk} \leq c_n) - E X_{nk} I(X_{nk} \leq c_n)] \\ &\quad + b_N^{-1} \sum_{n=k}^N a_n X_{nk} I(X_{nk} > c_n) + b_N^{-1} \sum_{n=k}^N a_n E X_{nk} I(X_{nk} \leq c_n). \end{aligned}$$

We eliminate the middle term of these three by again using the Borel-Cantelli lemma. Since $pk > 1$ we have

$$\begin{aligned} \sum_{n=k}^{\infty} P\{X_{nk} > c_n\} &= \sum_{n=k}^{\infty} \frac{p \cdot n!}{(n-k)!(k-1)!} \int_{c_n}^{\infty} (1-x^{-p})^{n-k} x^{-pk-1} dx \\ &< C \sum_{n=k}^{\infty} n^k \int_{c_n}^{\infty} x^{-pk-1} dx < C \sum_{n=k}^{\infty} \frac{n^k}{c_n^{pk}} \\ &= C \sum_{n=k}^{\infty} \frac{n^k}{(n^{1+1/p} \lg n)^{pk}} = C \sum_{n=k}^{\infty} \frac{n^k}{n^{pk+k} (\lg n)^{pk}} \\ &= C \sum_{n=k}^{\infty} \frac{1}{n^{pk} (\lg n)^{pk}} = C \sum_{n=k}^{\infty} \frac{1}{(n \lg n)^{pk}} < \infty. \end{aligned}$$

We next show that the first term vanishes almost surely. First, let

$1 < pk < 2$, then

$$\begin{aligned} &\sum_{n=k}^{\infty} c_n^{-2} E X_{nk}^2 I(X_{nk} \leq c_n) \\ &= \sum_{n=k}^{\infty} \frac{p \cdot n!}{c_n^2 (n-k)!(k-1)!} \int_1^{c_n} (1-x^{-p})^{n-k} x^{-pk+1} dx \\ &< C \sum_{n=k}^{\infty} \frac{n^k}{c_n^2} \int_1^{c_n} x^{-pk+1} dx < C \sum_{n=k}^{\infty} \frac{n^k}{c_n^2} c_n^{-pk+2} = C \sum_{n=k}^{\infty} \frac{n^k}{c_n^{pk}} < \infty \end{aligned}$$

as in the last calculation. If $pk = 2$, then

$$\sum_{n=k}^{\infty} c_n^{-2} E X_{nk}^2 I(X_{nk} \leq c_n) < C \sum_{n=k}^{\infty} \frac{n^k}{c_n^2} \lg c_n < C \sum_{n=k}^{\infty} \frac{n^k \lg n}{n^{2+2/p} (\lg n)^2}$$

$$= C \sum_{n=k}^{\infty} \frac{1}{n^2 \lg n} < \infty.$$

Finally, if $pk > 2$, then

$$\begin{aligned} & \sum_{n=k}^{\infty} c_n^{-2} EX_{nk}^2 I(X_{nk} \leq c_n) \\ &= \sum_{n=k}^{\infty} \frac{p \cdot n!}{c_n^2 (n-k)! (k-1)!} \int_1^{c_n} (1-x^{-p})^{n-k} x^{-pk+1} dx \\ &= \sum_{n=k}^{\infty} \frac{p \cdot n!}{c_n^2 (n-k)! (k-1)!} \sum_{j=0}^{n-k} \binom{n-k}{j} (-1)^j \int_1^{c_n} x^{-p(j+k)+1} dx \\ &= \sum_{n=k}^{\infty} \frac{p \cdot n!}{c_n^2 (n-k)! (k-1)!} \sum_{j=0}^{n-k} \frac{\binom{n-k}{j} (-1)^j}{p(j+k)-2} \\ & \quad + \sum_{n=k}^{\infty} \frac{p \cdot n!}{c_n^2 (n-k)! (k-1)!} \sum_{j=0}^{n-k} \frac{\binom{n-k}{j} (-1)^{j+1} c_n^{-p(j+k)+2}}{p(j+k)-2}. \end{aligned}$$

Using both our lemmas, with $m = k - 2/p$, the first term is

$$\begin{aligned} & \sum_{n=k}^{\infty} \frac{n!}{c_n^2 (n-k)! (k-1)!} \sum_{j=0}^{n-k} \frac{\binom{n-k}{j} (-1)^j}{j+m} \\ &= \sum_{n=k}^{\infty} \left(\frac{n!}{c_n^2 (n-k)! (k-1)!} \right) \left(\frac{(n-k)! \Gamma(m)}{\Gamma(n-k+m+1)} \right) \\ &< C \sum_{n=k}^{\infty} \frac{\Gamma(n+1)}{c_n^2 \Gamma(n-k+m+1)} < C \sum_{n=k}^{\infty} \frac{n^{-m+k}}{c_n^2} \\ &= C \sum_{n=k}^{\infty} \frac{n^{2/p}}{n^{2+2/p} (\lg n)^2} = C \sum_{n=k}^{\infty} \frac{1}{(n \lg n)^2} < \infty. \end{aligned}$$

As for the second term in our truncated second moment, we have

$$\begin{aligned} & \left| \sum_{n=k}^{\infty} \frac{p \cdot n!}{c_n^2 (n-k)! (k-1)!} \sum_{j=0}^{n-k} \frac{\binom{n-k}{j} (-1)^{j+1} c_n^{-p(j+k)+2}}{p(j+k)-2} \right| \\ &< C \sum_{n=k}^{\infty} \frac{n^k}{c_n^2} \sum_{j=0}^{n-k} \frac{\binom{n-k}{j}}{p(j+k)-2} = C \sum_{n=k}^{\infty} \frac{n^k}{c_n^{pk}} \sum_{j=0}^{n-k} \binom{n-k}{j} [c_n^{-p}]^j \end{aligned}$$

$$\begin{aligned}
&= C \sum_{n=k}^{\infty} \frac{n^k}{c_n^{pk}} [1 + c_n^{-p}]^{n-k} < C \sum_{n=k}^{\infty} \frac{n^k}{c_n^{pk}} \\
&= C \sum_{n=k}^{\infty} \frac{n^k}{n^{pk+k} (\lg n)^{pk}} = C \sum_{n=k}^{\infty} \frac{1}{(n \lg n)^{pk}} < \infty
\end{aligned}$$

establishing that the first term in our partition is almost surely negligible.

All that remains, is to determine where our truncated first moment is going

$$\begin{aligned}
EX_{nk} I(X_{nk} \leq c_n) &= \frac{p \cdot n!}{(n-k)!(k-1)!} \int_1^{c_n} (1-x^{-p})^{n-k} x^{-pk} dx \\
&= \frac{p \cdot n!}{(n-k)!(k-1)!} \sum_{j=0}^{n-k} \binom{n-k}{j} (-1)^j \int_1^{c_n} x^{-p(j+k)} dx \\
&= \frac{p \cdot n!}{(n-k)!(k-1)!} \sum_{j=0}^{n-k} \frac{\binom{n-k}{j} (-1)^j}{p(j+k) - 1} \\
&\quad + \frac{p \cdot n!}{(n-k)!(k-1)!} \sum_{j=0}^{n-k} \frac{\binom{n-k}{j} (-1)^{j+1} c_n^{-p(j+k)+1}}{p(j+k) - 1}.
\end{aligned}$$

Using our lemmas, with $m = k - 1/p$, the first term equals

$$\begin{aligned}
\frac{n!}{(n-k)!(k-1)!} \sum_{j=0}^{n-k} \frac{\binom{n-k}{j} (-1)^j}{j+m} &= \left(\frac{n!}{(n-k)!(k-1)!} \right) \left(\frac{(n-k)! \Gamma(m)}{\Gamma(n-k+m+1)} \right) \\
&= \frac{\Gamma(k-1/p) \Gamma(n+1)}{(k-1)! \Gamma(n+1-1/p)} \\
&\sim \frac{\Gamma(k-1/p)}{(k-1)!} \cdot n^{1/p}.
\end{aligned}$$

The other term in our first moment is bounded above by

$$\begin{aligned}
&\left| \frac{p \cdot n!}{(n-k)!(k-1)!} \sum_{j=0}^{n-k} \frac{\binom{n-k}{j} (-1)^{j+1} c_n^{-p(j+k)+1}}{p(j+k) - 1} \right| \\
&< C n^k \sum_{j=0}^{n-k} \binom{n-k}{j} c_n^{-p(j+k)+1} < C n^k c_n^{-pk+1} = \frac{C n^k c_n}{c_n^{pk}}
\end{aligned}$$

$$= \frac{Cn^k n^{1+1/p} \lg n}{n^{pk+k} (\lg n)^{pk}} = \frac{Cn^{1/p}}{n^{pk-1} (\lg n)^{pk-1}} = \frac{Cn^{1/p}}{(n \lg n)^{pk-1}} = o(n^{1/p})$$

since $pk > 1$. Thus

$$EX_{nk} I(X_{nk} \leq c_n) \sim \frac{\Gamma(k-1/p)}{(k-1)!} \cdot n^{1/p}.$$

Therefore, with probability one

$$\begin{aligned} \frac{\sum_{n=k}^N a_n X_{nk}}{b_N} &\sim \frac{\sum_{n=k}^N a_n EX_{nk} I(X_{nk} \leq c_n)}{b_N} \\ &\sim \frac{\Gamma(k-1/p)}{(k-1)!} \cdot \frac{\sum_{n=k}^N n^{-1-1/p} (\lg n)^a n^{1/p}}{(\lg N)^{a+1}} \\ &= \left(\frac{\Gamma(k-1/p)}{(k-1)!} \right) \cdot \left(\frac{\sum_{n=k}^N n^{-1} (\lg n)^a}{(\lg N)^{a+1}} \right) \rightarrow \frac{\Gamma(k-1/p)}{(a+1)(k-1)!} \end{aligned}$$

as $N \rightarrow \infty$, which completes this proof.

4. pk equal to one. It is surprising that in this section we are still able to obtain a Strong Law of Large Numbers. (For if $pk < 1$ we cannot even obtain a similar Weak Law, see Section 5.) However, in this case our weights, a_n , cannot be one. Theorem 3 shows why we need to study weighted sums of random variables. In this situation, from Adler [2], we have

Theorem 3. *If $pk = 1$ and $a > -2$, then*

$$\lim_{N \rightarrow \infty} \frac{\sum_{n=k}^N (\lg n)^a n^{-k-1} X_{nk}}{(\lg N)^{a+2}} = \frac{1}{(a+2)k!} \quad \text{almost surely.}$$

However, we are not so fortunate when $pk < 1$.

5. pk less than one. In this situation we show that even a “fair” ($L > 0$) Weak Law of Large Numbers fails to hold under the mildest of all assumptions. Clearly (2) holds in all our comparable Strong Laws.

Theorem 4. *If $pk < 1$ and a_n and b_N are positive constants where*

$$(2) \quad \max_{k \leq n \leq N} na_n^p = o(b_N^p)$$

then the only finite limit of our normalized sums is zero, i.e.,

$$\frac{\sum_{n=k}^N a_n X_{nk}}{b_N} \xrightarrow{P} 0.$$

Proof. Let m_n be the median from the density of X_{nk} . We first show that

$$(3) \quad \max_{k \leq n \leq N} \left(\frac{a_n m_n}{b_N} \right) \rightarrow 0$$

as $N \rightarrow \infty$. By definition

$$\begin{aligned} \frac{1}{2} &= \frac{p \cdot n!}{(n-k)!(k-1)!} \int_{m_n}^{\infty} (1-x^{-p})^{n-k} x^{-pk-1} dx \\ &< \frac{pn^k}{(k-1)!} \int_{m_n}^{\infty} x^{-pk-1} dx < \frac{n^k}{k!} m_n^{-pk}. \end{aligned}$$

Thus $m_n < Cn^{1/p}$. So

$$\frac{\max_{k \leq n \leq N} a_n m_n}{b_N} < \frac{C \max_{k \leq n \leq N} a_n n^{1/p}}{b_N} \rightarrow 0$$

by (2), establishing (3). Assuming that a Weak Law holds we have, by the Degenerate Convergence Theorem, see Chow and Teicher [3], page 338

$$\begin{aligned} 0 &\leftarrow \sum_{n=k}^N P\{X_{nk} > b_N/a_n\} \\ &= \frac{p}{(k-1)!} \sum_{n=k}^N \frac{n!}{(n-k)!} \int_{b_N/a_n}^{\infty} (1-x^{-p})^{n-k} x^{-pk-1} dx \\ &= \frac{p}{(k-1)!} \sum_{n=k}^N \frac{n!}{(n-k)!} \sum_{j=0}^{n-k} \binom{n-k}{j} (-1)^j \int_{b_N/a_n}^{\infty} x^{-p(j+k)-1} dx \\ &= \frac{p}{(k-1)!} \sum_{n=k}^N \frac{n!}{(n-k)!} \sum_{j=0}^{n-k} \frac{\binom{n-k}{j} (-1)^j (a_n/b_N)^{p(j+k)}}{p(j+k)} \end{aligned}$$

$$\begin{aligned}
&= \frac{1}{(k-1)!} \sum_{n=k}^N \frac{n!}{(n-k)!} \left(\frac{a_n}{b_N}\right)^{pk} \left[\frac{1}{k} + \sum_{j=1}^{n-k} \frac{\binom{n-k}{j} (-1)^j}{j+k} \left(\frac{a_n}{b_N}\right)^{pj} \right] \\
&> C \sum_{n=k}^N \frac{n!}{(n-k)!} \left(\frac{a_n}{b_N}\right)^{pk}
\end{aligned}$$

since the second sum is negligible, as we are about to show. Let $0 < \epsilon < 1/2$.

For all large N we have from (2) that $na_n^p < \epsilon b_n^p$, whence

$$\begin{aligned}
\left| \sum_{j=1}^{n-k} \frac{\binom{n-k}{j} (-1)^j}{j+k} \left(\frac{a_n}{b_N}\right)^{pj} \right| &< \sum_{j=1}^{n-k} \binom{n-k}{j} \left(\frac{a_n}{b_N}\right)^{pj} < \sum_{j=1}^{n-k} (n-k)^j \left(\frac{a_n}{b_N}\right)^{pj} \\
&< \sum_{j=1}^{\infty} n^j \left(\frac{a_n}{b_N}\right)^{pj} = \sum_{j=1}^{\infty} \left(\frac{na_n^p}{b_N^p}\right)^j < \sum_{j=1}^{\infty} \epsilon^j < 2\epsilon.
\end{aligned}$$

Therefore

$$(4) \quad \sum_{n=k}^N \frac{n!}{(n-k)!} \left(\frac{a_n}{b_N}\right)^{pk} \rightarrow 0.$$

Finally, by once again utilizing the Degenerate Convergence Theorem, we have as the weak limit of (1)

$$\begin{aligned}
\lim_{N \rightarrow \infty} \sum_{n=k}^N \frac{a_n}{b_N} EX_{nk} I(X_{nk} \leq b_N/a_n) &< \lim_{N \rightarrow \infty} \frac{C}{b_N} \sum_{n=k}^N \frac{a_n n!}{(n-k)!} \int_1^{b_N/a_n} x^{-pk} dx \\
&< \lim_{N \rightarrow \infty} \frac{C}{b_N} \sum_{n=k}^N \frac{a_n n!}{(n-k)!} \left(\frac{b_N}{a_n}\right)^{-pk+1} = \lim_{N \rightarrow \infty} \frac{C}{b_N^{pk}} \sum_{n=k}^N \frac{a_n^{pk} n!}{(n-k)!} = 0
\end{aligned}$$

by (4), which completes the proof.

6. Discussion. A comment should be made as to why different results occur as to whether pk is greater, equal or less than one. If pk exceeds one then EX_{nk} is finite and typical laws of large number do exist as shown in this paper. When $pk = 1$, then EX_{nk} is infinite, but barely which sometimes allows us to obtain unusual laws of large numbers (see Adler [2]). We say a random variable's expectation is barely infinite if $EX = \infty$ while $EX^{1-\epsilon} <$

∞ for any $\epsilon > 0$. Now, when $pk < 1$ we have $EX_{nk} = \infty$, but not barely, which surprisingly does not allow us to establish any kind of law of large numbers, whether it be of the strong or weak type.

Acknowledgement. I would like to thank the referee for his/her kind remarks. And also for the suggestion of adding a discussion as to why these laws of large numbers do and do not exist. That was an excellent idea.

References

1. M. Abrahmowitz and A. Stegun, *Handbook of Mathematical Functions*, 9th edition, Dover, New York, 1970.
2. A. Adler, *An unusual strong law of large numbers for the largest observation of a triangular array*, Bull. Instit. Math. Acad. Sinica, **29** (2001), 225-229.
3. Y. S. Chow and H. Teicher, *Probability Theory: Independence, Interchangeability, Martingales*, 2nd ed., Springer-Verlag, New York, 1988.
4. W. Feller, *An Introduction to Probability Theory and Its Applications*, Vol. 2, 2nd ed., John Wiley, New York, 1971.
5. J. Riordan, *Combinatorial Identities*, 2nd ed., Kreiger, New York, 1979.
6. E. Seneta, *Regularly Varying Functions*, Lecture Notes in Mathematics No. 508, Springer-Verlag, New York, 1976.

Department of Mathematics, Illinois Institute of Technology, Chicago, Illinois, 60616, U.S.A.