## **140** Chapter 4 Expected Values

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## THEOREM A

uppose that 
$$U = a + \sum_{i=1}^{n} b_i X_i$$
 and  $V = c + \sum_{j=1}^{m} d_j Y_j$ . Then  

$$\operatorname{Cov}(U, V) = \sum_{i=1}^{n} \sum_{j=1}^{m} b_i d_j \operatorname{Cov}(X_i, Y_j)$$

This theorem has many applications. In particular, since Var(X) = Cov(X, X),

$$Var(X + Y) = Cov(X + Y, X + Y)$$
$$= Var(X) + Var(Y) + 2Cov(X, Y)$$

More generally, we have the following result for the variance of a linear combination of random variables.

COROLLARY **A**  $\operatorname{Var}(a + \sum_{i=1}^{n} b_i X_i) = \sum_{i=1}^{n} \sum_{j=1}^{n} b_i b_j \operatorname{Cov}(X_i, X_j).$ 

If the  $X_i$  are independent, then  $Cov(X_i, X_j) = 0$  for  $i \neq j$ , and we have another corollary.

COROLLARY **B** Var $(\sum_{i=1}^{n} X_i) = \sum_{i=1}^{n} \text{Var}(X_i)$ , if the  $X_i$  are independent.

Corollary B is very useful. Note that  $E(\sum X_i) = \sum E(X_i)$  whether or not the  $X_i$  are independent, but it is generally *not* the case that  $Var(\sum X_i) = \sum Var(X_i)$ .

EXAMPLE **B** Finding the variance of a binomial random variable from the definition of variance and the frequency function of the binomial distribution is not easy (try it). But expressing a binomial random variable as a sum of independent Bernoulli random variables makes the computation of the variance trivial. Specifically, if *Y* is a binomial random variable, it can be expressed as  $Y = X_1 + X_2 + \cdots + X_n$ , where the  $X_i$  are independent Bernoulli random variables with  $P(X_i = 1) = p$ . We saw earlier (Example A in Section 4.2) that  $Var(X_i) = p(1 - p)$ , from which it follows from Corollary B that Var(Y) = np(1 - p).

## EXAMPLE **C** Random Walk

A drunken walker starts out at a point  $x_0$  on the real line. He tages the point  $X_1$ , which is a random variable with expected value  $\mu$  and variable, and his position