

opposite directions. If the angle  $\theta$  between the vectors  $\mathbf{x}$  and  $\mathbf{y}$  is a right angle, its cosine is 0, and so, from (2.07), the scalar product  $\langle \mathbf{x}, \mathbf{y} \rangle$  is 0. Conversely, if  $\langle \mathbf{x}, \mathbf{y} \rangle = 0$ , then  $\cos \theta = 0$  unless  $\mathbf{x}$  or  $\mathbf{y}$  is a zero vector. If  $\cos \theta = 0$ , it follows that  $\theta = \pi/2$ . Thus, if two nonzero vectors have a zero scalar product, they are at right angles. Such vectors are often said to be **orthogonal**, or, less commonly, **perpendicular**. This definition implies that the zero vector is orthogonal to everything.

Since the cosine function can take on values only between  $-1$  and  $1$ , a consequence of (2.07) is that

$$|\mathbf{x}^\top \mathbf{y}| \leq \|\mathbf{x}\| \|\mathbf{y}\|. \quad (2.08)$$

This result, which is called the **Cauchy-Schwartz inequality**, says that the absolute value of the inner product of  $\mathbf{x}$  and  $\mathbf{y}$  can never be greater than the length of the vector  $\mathbf{x}$  times the length of the vector  $\mathbf{y}$ . Only if  $\mathbf{x}$  and  $\mathbf{y}$  are parallel does the inequality in (2.08) become the equality (2.05). Readers are asked to prove this result in Exercise 2.2.

### Subspaces of Euclidean Space

For arbitrary positive integers  $n$ , the elements of an  $n$ -vector can be thought of as the coordinates of a point in  $E^n$ . In particular, in the regression model (2.01), the regressand  $\mathbf{y}$  and each column of the matrix of regressors  $\mathbf{X}$  can be thought of as vectors in  $E^n$ . This makes it possible to represent a relationship like (2.01) geometrically.

It is obviously impossible to represent all  $n$  dimensions of  $E^n$  physically when  $n > 3$ . For the pages of a book, even three dimensions can be too many, although a proper use of perspective drawings can allow three dimensions to be shown. Fortunately, we can represent (2.01) without needing to draw in  $n$  dimensions. The key to this is that there are only three vectors in (2.01):  $\mathbf{y}$ ,  $\mathbf{X}\boldsymbol{\beta}$ , and  $\mathbf{u}$ . Since only two vectors,  $\mathbf{X}\boldsymbol{\beta}$  and  $\mathbf{u}$ , appear on the right-hand side of (2.01), only two dimensions are needed to represent it. Because  $\mathbf{y}$  is equal to  $\mathbf{X}\boldsymbol{\beta} + \mathbf{u}$ , these two dimensions suffice for  $\mathbf{y}$  as well.

To see how this works, we need the concept of a **subspace** of a Euclidean space  $E^n$ . Normally, such a subspace has a dimension lower than  $n$ . The easiest way to define a subspace of  $E^n$  is in terms of a set of **basis vectors**. A subspace that is of particular interest to us is the one for which the columns of  $\mathbf{X}$  provide the basis vectors. We may denote the  $k$  columns of  $\mathbf{X}$  as  $\mathbf{x}_1, \mathbf{x}_2, \dots, \mathbf{x}_k$ . Then the subspace associated with these  $k$  basis vectors is denoted by  $\mathcal{S}(\mathbf{X})$  or  $\mathcal{S}(\mathbf{x}_1, \dots, \mathbf{x}_k)$ . The basis vectors are said to **span** this subspace, which in general is a  $k$ -dimensional subspace.

The subspace  $\mathcal{S}(\mathbf{x}_1, \dots, \mathbf{x}_k)$  consists of every vector that can be formed as a **linear combination** of the  $\mathbf{x}_i$ ,  $i = 1, \dots, k$ . Formally, it is defined as

$$\mathcal{S}(\mathbf{x}_1, \dots, \mathbf{x}_k) \equiv \left\{ \mathbf{z} \in E^n \mid \mathbf{z} = \sum_{i=1}^k b_i \mathbf{x}_i, \quad b_i \in \mathbb{R} \right\}. \quad (2.09)$$