CHAPTER 6

PRODUCTION DECISIONS AND THE SHORT-RUN DEMAND FOR WORKERS

6.1 Introduction

In the model developed in ch. 3 little was said about the production decisions of firms. The change in the number of workers employed was taken to be a function of current and expected future output changes, but the factors which determine the change in output were not discussed. Implicit in the specification of eq. (3.9) is the assumption that production decisions are in no way influenced by the number of workers on hand. Such factors as the level of inventories, the backlog of unfilled orders, and expected future sales are likely to influence production decisions, and if these decisions are also influenced by the number of workers on hand, then the one-way causality from decisions on production to decisions on employment implied by eq. (3.9) is not valid. This is not to say that in order for eq. (3.9) to be valid production has to be "exogenous" in the sense that firms have no control over the amount they produce, but only that among the factors which influence production decisions the number of workers on hand is not one of them.

HOLT, MODIGLIANI, MUTH, and SIMON (1960) – (hereafter referred to as HMMS) – in a path-breaking work on production and employment decisions have developed a model in which the level of sales is taken to be exogenous and in which decisions on production and employment are made simultaneously. Their model is actually a normative one – a model of how firms ought to behave in order to maximize profits – as opposed to a descriptive one – a model of how firms do in fact behave. Nevertheless, the HMMS model can be interpreted as a descriptive one and tested to see if firms do behave the way the model suggests they should. In this chapter the HMMS model is described and tested, and using the HMMS model as a guide, an alternative model to that developed in ch. 3 is also described and tested. The results achieved using the HMMS model are compared with the results achieved using the alternative model developed in this chapter, and then both of these sets of results are compared with the results achieved using the model developed in ch. 3. The chapter concludes with a discussion of some results achieved using Bureau of Census data.

6.2 The Holt, Modigliani, Muth, and Simon model

HMMS specify a quadratic cost function for the firm and then minimize the sum of expected future costs with respect to the relevant decision variables, production and employment, to arrive at equations determining the amount of output to produce and the size of the work force. They take sales and prices as exogenous, so that minimizing costs is equivalent to maximizing profits. Their cost function is composed of the following items:[1]

Regular payroll cost:

$$w_1 M_t + A_0, \tag{6.1}$$

where M_t is the size of the work force, w_1 is the wage rate, and A_0 is the "fixed cost term".

Cost of hiring and layoffs:

$$\lambda_0(M_t - M_{t-1} - A_1)^2. \tag{6.2}$$

The costs in (6.2) are the costs associated with changing the size of the work force in any one period. The constant term A_1 provides for asymmetry in costs of hiring and firing.

Expected cost of overtime (given M_t):

$$\lambda_1(Y_t - v_0 M_t)^2 + v_1 Y_t - v_2 M_t + v_3 Y_t M_t. \tag{6.3}$$

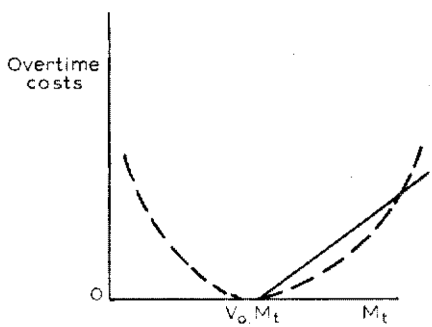

Fig. 6.1. Holt, Modigliani, Muth, and Simon's overtime cost approximation.

[1] See Holt *et al.* (1960, pp. 47–130).

The cost of overtime in eq. (6.3) depends both on the size of the work force, M_t, and on the amount of output produced, Y_t. The cost relation of which (6.3) is an approximation is presented in figure 6.1. Given M_t and the average output per worker v_0, $v_0 M_t$ is the maximum amount of output which can be produced without working overtime. At levels of output higher than this the cost of overtime rises, the cost depending on the size of the overtime premium. HMMS argue that random disturbances and discontinuities will smooth out the solid line in figure 6.1. The dotted line in figure 6.1 is the quadratic approximation given in (6.3). HMMS do point out that to the extent that production falls to a low level of output relative to the work force the approximation becomes poor.[1] Since (6.3) is based on a given size of the work force, M_t, there is a family of overtime cost curves, one for each value of M_t.

HMMS next define net inventories as inventories minus back orders and assume that the optimal level of net inventories equals $v_4 + v_5 S_t$, where S_t is the aggregate order rate. As the actual level of net inventories deviates from optimal in either direction, costs rise, and they postulate the following costs.

Expected inventory, back order, and set up costs:

$$\lambda_2[V_t - (v_4 + v_5 S_t)]^2, \qquad (6.4)$$

where V_t is the level of net inventories.

The HMMS cost function is the sum of eqs. (6.1)–(6.4). Since future orders are uncertain, the problem is to minimize the expected value of the sum of future costs with respect to the employment and production variables, subject to certain initial and terminal conditions. This minimization procedure yields the following two linear equations:

$$Y_t = \zeta_0 + \zeta_1 M_{t-1} + \zeta_2 V_{t-1} + \sum_{i=1}^{n} \psi_i S^e_{t+i}, \qquad (6.5)$$

$$M_t = \alpha'_0 + \alpha'_1 M_{t-1} + \rho'_0 V_{t-1} + \sum_{i=1}^{n} \gamma'_i S^e_{t+i}. \qquad (6.6)$$

S^e_{t+i} is the level of orders expected for period $t + i$, and n is the length of the decision period. Because of the quadratic nature of the cost function, the decisions reached by minimizing the sum of expected future costs using

[1] HOLT *et al.* (1960, p. 55, footnote 6).

merely the expected values of the S^e_{t+i} are the same as the decisions which would be reached using complete knowledge of the probability distribution functions of the S^e_{t+i}.

In the employment equation (6.6), which is of concern here, the number of workers employed during period t is seen to be a function of the number employed during period $t-1$, the level of net inventories at the end of period $t-1$, and expected future orders. α_1' in eq. (6.6) is expected to be positive under the HMMS interpretation, and ρ_0' is expected to be negative. Taking the functional form of eq. (6.6) to be log-linear instead of linear and taking first differences yields the following equation:[1]

$$\log M_t - \log M_{t-1} = \theta_0' + \alpha_1'(\log M_{t-1} - \log M_{t-2}) + \rho_0(\log V_{t-1} - \log V_{t-2}) + \gamma_0(\log S^e_t - \log S_{t-1}) + \sum_{i=1}^{n} \gamma_i'(\log S^e_{t+i} - \log S^e_{t+i-1}). \qquad (6.7)$$

This equation will be discussed in more detail below.

The main drawback to the HMMS approach would appear to be their quadratic approximation to overtime costs, eq. (6.3). As mentioned above, they state that this approximation is poor to the extent that production falls to a low level of output relative to the work force, but they add that the approximation may be good in the "relevant range".[2] In the previous chapters, however, it has been seen that output does fall to a low level relative to the work force in the course of the year, and if the assumptions made in this study are true, firms hold a considerable amount of positive excess labor during much of the year. This implies that the HMMS approximation (6.3) is a very poor one indeed, and a model derived from this approximation is likely to be unrealistic. Fortunately, the HMMS model can be compared with the model developed in ch. 3 by estimating an equation like (6.7) when data on sales and inventories are available. Before these estimates are made, however, an alternative model to that developed in ch. 3 will be described. This model is in the spirit of the HMMS model in that production decisions are not assumed to be independent of the size of the work force, but it avoids their unrealistic overtime cost approximation.

[1] The constant term θ'_0 has been added to eq. (6.7) to allow for the possibility of a time trend in log M_t.

[2] HOLT *et al.* (1960, p. 55, footnote 6).

6.3 An alternative model of the short-run demand for production workers

The model developed in this section is similar to the model developed in ch. 3 except that here expected future changes in sales (or shipments) rather than expected future changes in output are assumed to be the basic determinants of the change in the number of workers employed. In addition, the stock of inventories on hand is assumed to be a significant factor determining the change in the number of workers employed. Let S^e_{2wt+i} denote the level of sales expected for the second week of month $t + i$, V_{2wt-1} the actual stock of inventories on hand at the end of the second week of month $t - 1$, and V^d_{2wt-1} the desired stock of inventories on hand for the end of the second week of month $t - 1$. Then the basic equation determining $\log M_{2wt} - \log M_{2wt-1}$ is assumed to be

$$\log M_{2wt} - \log M_{2wt-1} =$$

$$\alpha_1''(\log M_{2wt-1} - \log M^d_{2wt-1}) + \sum_{i=1}^{m} \beta_i''(\log Y_{2wt-i} - \log Y_{2wt-i-1})$$

$$+ \rho_0''(\log V_{2wt-1} - \log V^d_{2wt-1}) + \gamma_0''(\log S^e_{2wt} - \log S_{2wt-1})$$

$$+ \sum_{i=1}^{n} \gamma_i''(\log S^e_{2wt+i} - \log S^e_{2wt+i-1}). \tag{6.8}$$

In eq. (6.8) the excess labor variable and the past output change variables have been left as they are in eq. (3.9) of the model developed in ch. 3; the expected future sales variables have replaced the expected future output variables; and $\log V_{2wt-1} - \log V^d_{2wt-1}$, which is the difference between the actual stock of inventories at the end of the second week of month $t - 1$ and the desired stock, has been added.

Another way of looking at eq. (6.8) is that it is similar to the HMMS equation (6.7) in that the change in the number of workers employed is taken to be a function of expected future changes in sales in both equations. In eq. (6.8), however, the excess labor variable has replaced the lagged dependent variable, $\log M_{t-1} - \log M_{t-2}$; the past output change variables have been added (to perhaps help depict the firm's reaction to the amount of excess labor on hand); and the inventory variable has been taken to be the difference between the actual and desired stock of inventories on hand rather than the past change in the stock on hand, $\log V_{t-1} - \log V_{t-2}$. Unlike the

HMMS equation, eq. (6.8) was not derived from the minimization of a particular cost function. As discussed in § 3.7, there is undoubtedly some cost function the minimization of which would yield an equation like (3.9) or (6.8), but it is likely to be quite complex. In order for HMMS to derive their equations from the minimization of a cost function, they are forced to make the quadratic approximation to overtime costs depicted in figure 6.1, which, as discussed above, is likely to be quite unrealistic.

The rationale for including the inventory variable, $\log V_{2wt-1} - \log V^d_{2wt-1}$, in the equation determining the change in the number of workers employed is the following. If the stock of inventories is, say, larger than desired, the firm will presumably draw down inventories, other things being equal, by producing less in the future. This implies that man-hour requirements will be less in the future than they would otherwise have been, which should have a negative effect on the current change in the number of workers employed. Conversely, if the stock of inventories is smaller than desired, the firm will presumably build up its inventories, other things being equal, by producing more in the future. This implies that man-hour requirements will be greater in the future than they would otherwise have been, which should have a positive effect on the current change in the number of workers employed. The relevant inventory variable to use in the equation would appear to be this $\log V_{2wt-1} - \log V^d_{2wt-1}$ variable, which measures how large or small the stock of inventories on hand is relative to the desired stock, and not the HMMS variable, $\log V_{t-1} - \log V_{t-2}$, which merely measures how large or small the change in the stock of inventories (from whatever level) has been.

The desired stock of inventories V^d_{2wt-1} is, of course, not directly observed, and some approximation for it must be found. Inventories can be used to meet part of any expected increase in sales, and by the accumulation and decumulation of inventories firms can smooth out fluctuations in production relative to fluctuations in sales. If sales were constant through time, finished goods inventories would really not be needed at all except for such things as insurance against a sudden increase in sales or a breakdown in production, and the desired stock of inventories could be taken to be constant through time. Since sales do fluctuate, it would appear that the desired stock of inventories will fluctuate also. If sales are expected to increase over the next few months, the desired stock of inventories is likely to be large so that part of the increase in sales can come from drawing down inventories rather than by increasing production to the full extent of the increase in sales, and if sales are expected to decrease over the next few months, the desired stock of inventories is likely to be small so that part of the decrease in sales can come from building up inventories rather than by decreasing production to the full extent of the decrease in sales. If sales are traditionally lowest in January and highest in July, for example, one would expect that the desired stock of inventories for the end of January would be greater than the desired stock of inventories for the end of July as firms attempt to smooth fluctuations in production relative to fluctuations in sales by accumulating and decumulating inventories throughout the year. The desired stock of inventories is thus assumed to be a function of expected future changes in sales:

$$\log V^d_{2wt-1} = \log \bar{V} + \tau_0 t + \phi_0(\log S^e_{2wt} - \log S_{2wt-1}) + \sum_{i=1}^{n} \phi_i(\log S^e_{2wt+i} - \log S^e_{2wt+i-1}). \qquad (6.9)$$

The time trend has been added to eq. (6.9), since there may be unaccounted for trend factors affecting the desired stock of inventories.

The expression for $\log V^d_{2wt-1}$ in eq. (6.9) can be substituted into eq. (6.8), which merely adds a constant term and a time trend to the equation and changes slightly the interpretation of the coefficients of the expected future change in sales variables. Notice that if the ϕ_i coefficients are all zero in eq. (6.9) so that the desired stock of inventories is merely a slowly trending variable, substituting eq. (6.9) (erroneously) into eq. (6.8) will merely mean that the interpretation of the coefficients of the expected future change in sales variables is slightly wrong and will not bias the estimates in any way.

Eq. (6.8) is thus seen to combine the HMMS idea that expected future sales rather than expected future production should be considered to be the relevant exogenous variable affecting the level of the work force; the idea of the model of ch. 3 that firms react in a certain way to the amount of excess labor on hand; and the idea that the difference between the actual and desired stock of inventories should affect employment decisions. Given data on inventories and sales, eq. (6.8) and the HMMS equation (6.7) can be estimated and compared, and this will be done in § 6.5 after a discussion of the data in § 6.4.

It should perhaps be noted here that if no inventories are held in a particular industry, then the alternative model developed in this chapter [as exemplified by eq. (6.8)] and the model developed in ch. 3 [as exemplified by eq. (3.9)] are equivalent: the inventory variable disappears from eq. (6.8) and sales and production are the same. Of the industries considered in this study, the

Newspaper publishing and printing industry, 271, obviously holds no inventories to speak of, and it also appears to be the case that the Apparel industries, 231, 232, and 232, the Footwear industry, 314, and the Metal cans industry, 341, hold inventories only in small amounts relative to short-run changes in the amount of output produced.

6.4 The data

Let S_t denote the amount of output shipped (or sold) during month t, Y_t the amount produced during month t, and V_t the stock of inventories on hand at the end of month t. Then by definition

$$Y_t = S_t + V_t - V_{t-1}, \tag{6.10}$$

which says that the amount of output produced during month t is equal to the amount shipped during the month plus the amount by which the stock of inventories has been changed. It was mentioned in § 4.2 that when data were gathered from sources other than the FRB, the monthly figures were converted into average daily rates for the month using the FRB estimate of the number of working days in each month for each industry. Let d_t denote the number of working days in month t. (The construction of d_t is discussed in detail in the data appendix.) If eq. (6.10) is divided through by d_t, it can then be written

$$Y_{dt} = S_{dt} + (V_t - V_{t-1})_d, \tag{6.11}$$

where as before the subscript dt denotes the average daily rate for month t and where $(V_t - V_{t-1})_d$ denotes the average daily rate of inventory investment for month t. In table 6.1 the additional notation used in the rest of this chapter is presented.

For four of the industries considered in this study – the Tobacco industries, 211 and 212, and Tires and inner tubes industry, 301, and the Cement industry, 324 – sufficient data were available so that eqs. (6.7) and (6.8) could be estimated. It was mentioned in § 4.2 that for industries 301 and 324 output data (i.e., data on Y_t) were available from the Rubber Manufacturers Association (RMA) and the Bureau of Mines respectively. These data were used for the estimates presented in the previous chapters. From the RMA and the Bureau of Mines, data on the stock of inventories at the end of the month, V_t, were also available, which meant that for industries 301 and 324 data on S_t could be constructed from the data on Y_t and V_t using eq. (6.10). For industries 211 and 212, FRB data were used for the estimates presented

TABLE 6.1

Additional notation used in ch. 6

Y_t	the amount of output produced during month t.
S_t	the amount of goods sold during month t.
S_{2wt}	the amount of goods sold during the second week of month t.
S_{dt}	the average daily rate of sales for month t.
V_t	the stock of inventories on hand at the end of month t.
V_{2wt}	the stock of inventories on hand at the end of the second week of month t.
$(V_t - V_{t-1})_d$	the average daily rate of inventory investment for month t.
S^e_{2wt+i}	the amount of goods expected to be sold during the second week of month $t+i$ ($i = 0, 1, 2, \ldots$), the expectation being made during the second week of month $t-1$.
V^d_{2wt}	the desired stock of inventories on hand for the end of the second week of month t.

in the previous chapters, but data were also available from the Internal Revenue Service (IRS) on Y_t and S_t for each of these industries.[1]

From data on Y_t and S_t, data on the stock of inventories, V_t, cannot be constructed using eq. (6.10), and for industries 211 and 212 data on V_t were constructed in the following manner. For December 1965 (denoted as 6512) the ratio of the dollar value of shipments to the dollar value of the stock of inventories (denoted as R) was computed using Bureau of Census data on the Tobacco industry 21. For each industry, S_{6512} (IRS data) was divided by R to give a value of V_{6512} for each industry. Using this figure as a base for each industry, the other values of V_t were constructed using the formula [from eq. (6.10)], $V_{t-1} = V_t + S_t - Y_t$. Any errors resulting from this construction will merely mean that the values of V_t are off by a constant amount.

From the RMA, Bureau of Mines, and IRS, data were thus available on Y_t, S_t, and V_t for industries 301, 324, 211, and 212, and from these data and the data on d_t for each of the industries, data on $Y_{dt}(=Y_t/d_t)$ and $S_{dt}(=S_t/d_t)$ were also available. These data were used to estimate eqs. (6.7) and

[1] The FRB and IRS data are not independent data, since the FRB uses the IRS data to construct the production indices for industries 211 and 212. For this study the IRS data were collected from 1953 through 1965. Since the RMA, Bureau of Mines, and IRS data are not available in a convenient summary form anywhere, these data are presented in tabular form in the data appendix.

(6.8) after some necessary modifications of the equations were made. These modifications will be discussed in the next section before the equation estimates are presented.

6.5 Equation estimates

Neither the HMMS equation (6.7) nor eq. (6.8) is in an estimatable form, since not all of the variables in the equations are observed. Looking first at eq. (6.7), the observed M_{2w} variable can be used as the employment variable (in place of M) in the equation, and the observed S_d variable can be used as the sales variable (in place of S). Because M_{2w} is the number of workers employed during the second week and S_d is the average daily rate of sales for the entire month, for reasons analogous to those discussed in § 4.3, $\log S_{dt-1} - \log S_{dt-2}$ may be a significant determinant of $\log M_{2wt} - \log M_{2wt-1}$ in eq. (6.7) under the HMMS model, and this variable should be included in the equation. To be consistent with the other variables which are to be used in eq. (6.7), the inventory investment variable should be the average daily rate of inventory investment for the monthly decision period between the end of the second week of month $t-2$ and the end of the second week of month $t-1$, rather than the absolute amount of inventory investment for the period unadjusted for the number of working days. This rate, of course, has to be approximated by the average daily rate for month $t-1$, since data on the stock of inventories at the end of the second week are not available. The average daily rate of inventory investment for month $t-1$ is $(V_{t-1} - V_{t-2})/d_{t-1}$, where d_{t-1} is the number of working days in month $t-1$, and since eq. (6.7) is in log form, the inventory investment variable is taken to be $\log V_{t-1} - \log V_{t-2} - \log d_{t-1}$, which will be denoted as $(\log V_{t-1} - \log V_{t-2})_d$. For purposes of estimation eq. (6.7) thus becomes

$$\begin{aligned}\log M_{2wt} - \log M_{2wt-1} = \\ &\theta_0' + \alpha_1'(\log M_{2wt-1} - \log M_{2wt-2}) \\ &+ \rho_0'(\log V_{t-1} - \log V_{t-2})_d + \beta_1'(\log S_{dt-1} - \log S_{dt-2}) \\ &+ \gamma_0'(\log S_{dt}^e - \log S_{dt-1}) + \sum_{i=1}^{n} \gamma_i'(\log S_{dt+i}^e - \log S_{dt+i-1}^e). \qquad (6.7)'\end{aligned}$$

Eq. (6.7)′ is, of course, different depending on which expectational hypothesis is assumed.

Looking next at eq. (6.8), the observed Y_d variable can be used as the output variable in the equation (in place of Y_{2w}) and the observed S_d variable can be used as the sales variable (in place of S_{2w}). The unobserved stock of inventories at the end of the second week of month t − 1, V_{2wt-1}, can be approximated by the observed stock of inventories at the end of month t − 1, V_{t-1}. The desired stock of inventories in eq. (6.8) should thus be taken to be the desired stock for the end of month $t - 1$ (denoted, say, as V^d_{t-1}), and in eq. (6.9) for log V^d_{t-1}, the observed S_d variable can be used as the sales variable (in place of S_{2w}). From eq. (3.12) the excess labor variable in eq. (6.8), $\alpha_1''(\log M_{2wt-1} - \log M^d_{2wt-1})$, is equal to $\alpha_1''(\log M_{2wt-1} - \log M^*_{2wt-1}H^*_{2wt-1}) + \alpha_1'' \log \bar{H} + \alpha_1''\mu t$. Data for $M^*_{2wt-1}H^*_{2wt-1}$ were constructed in the manner described in § 3.6. In the construction of $M^*_{2wt-1}H^*_{2wt-1}$ for industries 301 and 324, the RMA and Bureau of Mines output data were used directly (after conversion into average daily rates), but for industries 211 and 212 the FRB data were used rather than the IRS data. Since the FRB data are constructed using the IRS data, no new relevant information is available from the IRS data with respect to the construction of $M^*_{2wt-1}H^*_{2wt-1}$ for industries 211 and 212, and so the values constructed in ch. 3 for these two industries using FRB data can be used here. For purposes of estimation, eq. (6.8) thus becomes [combining eqs. (6.8) and (6.9)]:

$$\begin{aligned}\log M_{2wt} - \log M_{2wt-1} = {} & (-\alpha_1'' \log \bar{H} - \rho_0 \log \bar{V}) \\ & + (\mu - \rho_0''\tau_1)t + \alpha_1''(\log M_{2wt-1} - \log M^*_{2wt-1}H^*_{2wt-1}) \\ & + \rho_0'' \log V_{t-1} + \sum_{i=1}^{m} \beta_i''(\log Y_{dt-i} - \log Y_{dt-i-1}) \\ & + (\gamma_0'' - \rho_0''\phi_0)(\log S^e_{dt} - \log S_{dt-1}) \\ & + \sum_{i=1}^{n} (\gamma_i'' - \rho_0''\phi_i)(\log S^e_{dt+i} - \log S^e_{dt+i-1}). \qquad (6.8)'\end{aligned}$$

Eq. (6.8)′ is also different depending on which expectational hypothesis is assumed.

For each industry the expectational hypothesis which gave the better results for eq. (3.9)′ in table 4.3 was assumed to be the correct one for that industry and was used in the estimation of eqs. (6.7)′ and (6.8)′. For the work here, of course, the expectational hypotheses were taken to be in terms of sales rather than production. In other words, eqs. (3.13) and (3.14) were taken to be in terms of S_d rather than Y_{2w}. For each industry the horizon

TABLE 6.2

Parameter estimates for eq. (6.7)′

Industry	No. of obs.	$\hat{\theta}'_0$	$\hat{\alpha}'_1$	$\hat{\rho}'_0$	$\hat{\beta}'_1$	$\hat{\gamma}'_0$	$\hat{\gamma}'_1$	$\hat{\gamma}'_2$	$\hat{\gamma}'_3$	$\hat{\gamma}'_4$	[a]$\hat{\delta}'$	R^2	SE	DW
211	96	−.080	.168	−.026		.038	−.010	.049			.013	.318	.0091	2.02
		(1.25)	(2.27)	(1.24)		(2.09)	(0.82)	(4.61)			(0.81)			
212	107	−.082	−.106	−.026	.090	.021						.190	.0187	1.64
		(0.78)	(1.84)	(0.76)	(3.84)	(0.84)								
301	134	−.023	.222	−.007		.003	.008	−.020	−.008			.095	.0162	2.01
		(0.39)	(2.68)	(0.36)		(0.26)	(0.67)	(1.76)	(0.76)					
324	187	−.004	.201	−.001	.056	.030	−.014	.025	.001	−.001	−.006	.378	.0234	2.08
		(0.07)	(2.90)	(0.07)	(4.22)	(2.56)	(1.15)	(2.28)	(0.05)	(0.10)	(0.31)			

t-statistics are in parentheses.

[a] $\hat{\delta}'$ is the coefficient estimate of $\log S_{dt-1} - \log S_{dt-13}$ under the non-perfect expectational hypothesis.

TABLE 6.3

Parameter estimates for eq. (6.8)′

Industry	No. of obs.	$\widehat{-\alpha''_1 \log \bar{H} - \varrho''_0 \log \bar{V}}$	$\hat{\alpha}''_1$	$\widehat{\mu-\varrho''_0\tau_1}$	$\hat{\rho}''_0$	$\hat{\beta}''_1$	$\widehat{\gamma''_0-\varrho''_0\varphi''_0}$	$\widehat{\gamma''_1-\varrho''_0\varphi''_1}$	$\widehat{\gamma''_2-\varrho''_0\varphi''_2}$	$\widehat{\gamma''_3-\varrho''_0\varphi''_3}$	$\widehat{\gamma''_4-\varrho''_0\varphi''_4}$	[a]$\hat{\delta}''$	R^2	SE	DW
211	96	[b]	−.072	−.061	−.033		.066	.013	.053			.004	.352	.0089	1.67
			(2.96)	(2.57)	(2.92)		(3.09)	(0.88)	(5.04)			(0.24)			
212	107	−.242	−.038	−.006	.001	.060	.036						.201	.0186	2.85
		(0.83)	(1.48)	(0.12)	(0.06)	(4.17)	(1.45)								
301	134	−.399	−.084	.036	−.010		.016	.010	−.014	.002			.278	.0145	1.80
		(4.58)	(5.97)	(0.91)	(2.52)		(1.76)	(1.03)	(1.38)	(0.26)					
324	187	.364	.003	.227	−.037	.156	.056	.007	.044	.000	−.010	.000	.522	.0205	2.40
		(2.65)	(0.14)	(3.81)	(4.97)	(9.10)	(4.16)	(0.57)	(4.28)	(0.03)	(0.99)	(0.01)			

t-statistics are in parentheses.

[a] $\hat{\delta}''$ is the coefficient estimate of $\log S_{dt-1} - \log S_{dt-13}$ under the non-perfect expectational hypothesis.

[b] The constant was excluded from the equation because of its strong collinearity with $\log V_{t-1}$.

TABLE 6.4

Parameter estimates for eq. (3.9)′

Industry	No. of obs.	$\widehat{\alpha_1 \log H}$	$\hat{\alpha}_1$	$1000\,\widehat{\alpha_1 \mu}$	$\hat{\beta}_1$	$\hat{\gamma}_0$	$\hat{\gamma}_1$	$\hat{\gamma}_2$	$\hat{\gamma}_3$	$\hat{\gamma}_4$	[a]$\hat{\delta}$	R^2	SE	DW
211	96	−.464	−.080	−.066		.083	.020	.052			.005	.401	.0085	1.55
		(3.47)	(3.52)	(2.93)		(4.21)	(1.52)	(5.69)			(0.34)			
212	107	−.430	−.073	−.018	.058	.088						.331	.0169	2.98
		(2.99)	(2.97)	(0.49)	(4.64)	(4.73)								
301	134	−.626	−.108	−.062		.055	.059	.030	.036			.297	.0142	1.92
		(7.20)	(7.18)	(2.79)		(2.88)	(3.37)	(1.83)	(2.29)					
324	187	−.653	−.110	.060		.224	.039	.026	.052	.051	.008	.639	.0177	2.01
		(6.37)	(6.34)	(2.44)		(16.50)	(2.40)	(1.60)	(3.36)	(3.42)	(0.47)			

t-statistics are in parentheses.

[a] $\hat{\delta}$ is the coefficient estimate of $\log Y_{at-1} - \log Y_{at-13}$ under the non-perfect expectational hypothesis.

(i.e., the size of n) over which the expectational variables were significant in the estimation of eq. (3.9)′ was used in the estimation of eqs. (6.7)′ and (6.8)′, even if not all of the expectation variables proved to be significant in the equations, in order that the various results could be compared. For eq. (6.7)′ $\log S_{dt-1} - \log S_{dt-2}$ was included in the final equation estimated only if it proved to be significant. For industries 301 and 324 the same period of estimation was used to estimate eqs. (6.7)′ and (6.8)′ as was used to estimate eq. (3.9)′ above, but for industries 211 and 212 a shorter period had to be used since the IRS data were only collected from 1953 on.

The results of estimating the HMMS equation (6.7)′ for industries 211, 212, 301, and 324 are presented in table 6.2; the results of estimating eq. (6.8)′ are presented in table 6.3; and for purposes of comparison, the results of estimating eq. (3.9)′ are presented in table 6.4. For industries 301 and 324 the results presented in table 6.4 are the same as those presented in table 4.3, but for industries 211 and 212 eq. (3.9)′ was re-estimated using the IRS data and the shorter period of estimation to insure a valid comparison with eqs. (6.7)′ and (6.8)′.

Looking at the HMMS equation first, the results in table 6.2 are not very good. The fits are low compared with those for eq. (3.9)′ in table 6.4; for none of the industries is the estimate of the coefficient ρ_0' of the inventory investment variable significant, although it is of the expected negative sign; for industry 212 the estimate of the coefficient α_0' of $\log M_{2wt-1} - \log M_{2wt-2}$ is not significant and is of the wrong sign; for industries 212 and 301 the estimate of the coefficient γ_0' of $\log S^e_{dt} - \log S_{dt-1}$ is not significant; and only two other of the expected future change in sales variables are significant.

Looking at the equation developed in this chapter next, the results presented in table 6.3 are somewhat better. The fits are better than those of the HMMS equation in table 6.2, but they are still not as good as those for eq. (3.9)′ in table 6.4. For industry 212 the estimate of the coefficient ρ_0'' of the inventory variable is not significant; the excess labor variable is significant only for industries 211 and 301; as was the case for the HMMS equation, only for industries 211 and 324 is the estimate of the coefficient γ_0'' of $\log S^e_{dt} - \log S_{dt-1}$ significant; and only two other of the expected future change in sales variables are significant in the table.

Turning finally to eq. (3.9)′, the results presented in table 6.4 are by far the best. The fits are much better; for every industry the excess labor variable is significant; for every industry the estimate of the coefficient

γ_0 of $\log Y^e_{dt} - \log Y_{dt-1}$ is significant; and for the most part the expected future change in output variables are significant.

Although the sample is small, the results achieved here strongly indicate that neither the HMMS model nor the alternative model developed in this chapter gives as good an explanation of short-run changes in the number of workers employed as the model developed in ch. 3. If one had to choose between the HMMS model and the model developed in this chapter, the latter gives consistently better results, but the model developed in ch. 3, in which decisions on production are assumed not to be influenced by the number of workers on hand, seems to dominate even this model. The results suggest, in other words, that models which specify a one-way causality from decisions on production to decisions on employment are more realistic than models which specify that these decisions are made simultaneously.

This conclusion should perhaps be qualified by noting that for industries 207, 332, 336, and about 34 percent of 331 the FRB data on production are really data on sales or shipments. The results presented in table 4.3 of estimating eq. (3.9)′ using these data are not noticeably worse than the results of estimating the other equations, and there is no way of knowing whether the use of data on production would have lead to better results for these industries, as would be expected from the results achieved in this chapter. Because of the small sample size, the conclusion of this chapter must remain somewhat tentative.

6.6 Bureau of Census data

For four of the seventeen industries considered in this study – 201, 301, 331, and 332 – unpublished Bureau of Census data on the value of shipments and the value of inventories were available monthly from 1948 or 1953 to the present. The basic disadvantage of these data compared with the FRB (or RMA or Bureau of Mines) data is that they are based on dollar values rather than physical magnitudes. Price deflators could be used, but the deflators themselves are of questionable accuracy. Moreover, the Census data are based on sample surveys, whereas most of the output data used in this study are based on the whole population. One of the reasons the three-digit Census data are not published is the questionable reliability of the estimates, particularly the estimates before 1960.

Nevertheless, the Bureau of Census data were used to estimate eq. (3.9)′ to see how the results compared with the results achieved using FRB or RMA data. The Census data were also used to estimate eq. (6.8)′ developed in this chapter to see if the same conclusion was reached using these data as was reached in the previous section, namely, that eq. (3.9)′ gives better results than eq. (6.8)′. From the Census data on the value of shipments for month t, S_t, and on the value of inventories at the end of month t, V_t, data on the value of production for month t, Y_t, were constructed using eq. (6.10). S_t and Y_t were then divided by d_t, the number of working days in month t, to yield the average daily rate of sales and production for month t, S_{dt} and Y_{dt}. This procedure is described in the data appendix.

As an example of how the Bureau of Census data compare with the data used in this study, for industry 201 the square of the correlation coefficient between the first differences (of the logs) of the FRB output series and the first differences (of the logs) of the Census output series over the sample period was only .001. For industry 331 it was .351. For industry 332 the square of the correlation coefficient between the first differences (of the logs) of the FRB (shipments) series and the Census shipments series was .338. For industry 301 the square of the correlation coefficient between the first differences (of the logs) of the Census output series and the RMA output series was .402, and between the first differences (of the logs) of the Census shipments series and the RMA shipments series it was .364. It is thus evident that the Census data and the FRB or RMA data are quite different, and the results achieved using Census data should be interpreted with caution.

The results of estimating eq. (3.9)′ using Census data are presented in table 6.5 for industries 201, 301, 331, and 322, along with the results of estimating the same equation using FRB or RMA data. For industries 201, 331, and 336 the Census data were available for a shorter period of time than the FRB data, and so eq. (3.9)′ was re-estimated using FRB data for the same period of estimation as was used for the Census data to insure a valid comparison. These are the results presented in table 6.5. For industry 301 the results presented in table 6.5 of estimating eq. (3.9)′ using RMA data are the same as the results presented in table 4.3 (and in table 6.4). When Census data were used to estimate the equation, the excess labor variable was constructed using the Census data on production instead of the FRB or RMA data. In the data appendix the exact periods of estimation which were used in table 6.5 are presented, and the months which were used as peaks in the output per paid-for man-hour interpolations when Census data were used are presented for each of the four industries. When estimating eq. (3.9)′, the same expectational variables were used here as were used in table 4.3, except for industry 331. For this industry when Census data were used, two expected future output change variables were significant which were not

TABLE 6.5

Parameter estimates for eq. (3.9)′ using (a) FRB or RMA data and (b) Bureau of Census data

Industry	No. of obs.	$\widehat{\alpha_1 \log \bar{H}}$	$\hat{\alpha}_1$	$\widehat{1000\,\alpha_1\mu}$	$\hat{\beta}_4$	$\hat{\beta}_3$	$\hat{\beta}_2$	$\hat{\beta}_1$	$\hat{\gamma}_0$	$\hat{\gamma}_1$	$\hat{\gamma}_2$	$\hat{\gamma}_3$	$\hat{\gamma}_4$	$\hat{\gamma}_5$	$\hat{\gamma}_6$	[a]$\hat{\delta}$	R^2	SE	DW
201	182(a)	−.979	−.168	.075			.066	.073	.259	.164	.109	.138	.153	.091	.064	.041	.643	.0120	1.86
		(4.02)	(4.02)	(3.31)			(3.36)	(3.77)	(9.25)	(6.53)	(4.43)	(6.84)	(8.71)	(5.58)	(3.45)	(2.12)			
	182(b)	−.422	−.073	−.042			.054	.087	.137	.126	.127	.126	.097	.049	.014	.021	.242	.0174	1.24
		(2.44)	(2.46)	(1.70)			(3.22)	(3.77)	(4.94)	(5.24)	(5.57)	(5.49)	(4.18)	(2.28)	(0.87)	(1.12)			
301	134(a)	−.626	−.108	−.062					.055	.059	.030	.036					.297	.0142	1.92
		(7.20)	(7.18)	(2.79)					(2.88)	(3.37)	(1.83)	(2.29)							
	134(b)	−.483	−.083	−.017					.073	.057	.033	.038					.196	.0152	1.66
		(4.77)	(4.76)	(0.81)					(3.63)	(2.97)	(1.71)	(2.40)							
331	118(a)	−.207	−.035	.006	.047	.067	.036	.124	.185								.794	.0103	1.90
		(2.93)	(2.89)	(0.33)	(3.39)	(4.63)	(2.37)	(6.17)	(9.61)										
	118(b)	−.010	−.016	.018	.034	.054	.062	.100	.133	.057	.030						.695	.0127	1.37
		(1.19)	(1.13)	(0.83)	(2.70)	(3.99)	(4.38)	(6.06)	(9.18)	(4.45)	(2.46)								
332	120(a)	−.642	−.108	.045					.167	.027	.040	.019	.025				.381	.0178	2.51
		(6.28)	(6.18)	(1.14)					(5.87)	(1.44)	(2.31)	(1.15)	(1.52)						
	120(b)	−.640	−.108	.047					.082	.064	.071	.032	.018				.354	.0182	2.59
		(6.60)	(6.50)	(1.18)					(5.19)	(4.20)	(5.04)	(2.53)	(1.78)						

t-statistics are in parentheses.

[a] $\hat{\delta}$ is the coefficient estimate of $\log Y_{dt-1} - \log Y_{dt-13}$ under the non-perfect expectational hypothesis.

TABLE 6.6

Parameter estimates for eq. (6.8)′ using Bureau of Census data

Industry	No. of obs.	$-\alpha''_1 \log \widehat{H - \rho''_0 \log \Delta}$	$\hat{\alpha}''_1$	$\widehat{\mu-\rho''_0\tau_1}$	$\hat{\beta}''_0$	$\hat{\beta}''_4$	$\hat{\beta}''_3$	$\hat{\beta}''_2$	$\hat{\beta}''_1$	$\widehat{\gamma''_0-\rho''_0\varphi''_0}$	$\widehat{\gamma''_1-\rho''_0\varphi''_1}$	$\widehat{\gamma''_2-\rho''_0\varphi''_2}$	$\widehat{\gamma''_3-\rho''_0\varphi''_3}$	$\widehat{\gamma''_4-\rho''_0\varphi''_4}$	$\widehat{\gamma''_5-\rho''_0\varphi''_5}$	$\widehat{\gamma''_6-\rho''_0\varphi''_6}$	${}^a\hat{\delta}''$	R^2	SE	DW
201	182	−.120	−.082	−.068	−.055			.010	.017	.077	.089	.116	.127	.083	.033	.011	.004	.223	.0177	1.08
		(0.73)	(2.66)	(2.59)	(4.52)			(0.51)	(0.61)	(2.22)	(2.67)	(3.51)	(3.64)	(2.53)	(1.17)	(0.57)	(0.19)			
301	134	−.227	−.060	.064	−.023					.032	.027	.008	.018					.147	.0157	1.63
		(1.45)	(3.18)	(1.22)	(1.54)					(1.71)	(1.56)	(0.48)	(1.08)							
331	118	.120	.000	.112	−.017	.034	.063	.069	.116	.130	.036	.013						.693	.0128	1.43
		(0.98)	(0.02)	(1.77)	(1.45)	(2.69)	(4.55)	(4.83)	(6.93)	(9.02)	(3.10)	(1.17)								
332	120	−.370	−.087	.112	−.027					.076	.053	.053	.028	.014				.322	.0187	2.66
		(2.70)	(5.73)	(1.81)	(1.41)					(3.99)	(2.87)	(2.93)	(1.71)	(1.05)						

t-statistics are in parentheses.

[a] $\hat{\delta}''$ is the coefficient estimate of $\log S_{at-1} - \log S_{at-13}$ under the non-perfect expectational hypothesis.

significant when FRB data were used, and these two variables were included in the equation which used Census data.

Comparing the results in table 6.5, it is seen that the use of FRB or RMA data yields better fits in all four industries, especially in industry 201 where the R^2 decreases from .643 using FRB data to .242 using Census data. Except for industry 331 the excess labor variable is significant in the equations which used Census data, and for the most part the expected future output change variables are significant as well. As was just mentioned, for industry 331 two of the expected future output change variables were significant when Census data were used which were not significant when FRB data were used. The over-all results indicate that while the use of Census data leads to poorer results than the use of FRB or RMA data, the Census data do not appear to be completely worthless.

Assuming, then, that the Census data are of some use, eq. (6.8)′ was estimated using the Census data, and the results are presented in table 6.6. For each industry the same expectational horizon was used in estimating eq. (6.8)′ as was used in table 6.5 for the Census data equations. The results in the two tables are thus directly comparable. Examining the results achieved using Census data in the two tables, it is seen that for all four industries eq. (3.9)′ give better results than eq. (6.8)′. Only for industry 201 is the inventory variable significant in eq. (6.8)′ in table 6.6, and for all of the industries the expected change in output variables in eq. (3.9)′ are more significant than the expected change in sales variable in eq. (6.8)′. The fit of eq. (3.9)′ is better than the fit of eq. (6.8)′ for all four industries. The results achieved here using Census data are, therefore, consistent with the results achieved in the previous section using IRS, RMA, and Bureau of Mines data: eq. (3.9) appears to be more realistic than eq. (6.8). Since the Census data are probably not as accurate as the other data, however, less reliance can be put on the results achieved here.

For a final comparison using the Census data, the HMMS equation (6.7)′ was estimated for the four industries using the same expectational variables as those used in table 6.6 for eq. (6.8)′. The results are presented in table 6.7. For eq. (6.7)′ $\log S_{dt-1} - \log S_{dt-2}$ was included in the final equation estimated only if it proved to be significant. Looking at the results in tables 6.6 and 6.7, the HMMS equation (6.7)′ gives poorer results than eq. (6.8)′ for three of the four industries. For industries 301, 331, and 332 the fit is worse for eq. (6.7)′ than for eq. (6.8)′; for 301 none of the expected future change in sales variables is significant in table 6.7 and the inventory variable is not significant; for industry 331 the inventory variable is not significant; and

TABLE 6.7

Parameter estimates for eq. (6.7)′ using Bureau of Census data

Industry	No. of obs.	$\hat{\theta}'_0$	$\hat{\alpha}'_1$	$\hat{\rho}'_0$	$\hat{\beta}'_1$	$\hat{\gamma}'_0$	$\hat{\gamma}'_1$	$\hat{\gamma}'_2$	$\hat{\gamma}'_3$	$\hat{\gamma}'_4$	$\hat{\gamma}'_5$	$\hat{\gamma}'_6$	[a]$\hat{\delta}'$	R^2	SE	DW
201	182	−.176	.436	−.055		−.039	−.017	.031	.066	.052	.020	.015	−.014	.286	.0168	2.00
		(2.53)	(6.36)	(2.54)		(1.93)	(0.66)	(1.07)	(2.05)	(1.73)	(0.76)	(0.85)	(0.68)			
301	134	−.173	.215	−.054		−.005	.025	.005	.017					.088	.0162	1.96
		(1.56)	(2.64)	(1.55)		(0.26)	(1.41)	(0.30)	(1.02)							
331	118	.003	.462	.001	.055	.095	.033	.022						.613	.0141	2.13
		(0.02)	(6.36)	(0.04)	(3.09)	(5.68)	(2.65)	(1.88)								
332	120	.319	−.023	.104		.066	.040	.042	.027	.014				.150	.0208	2.15
		(2.89)	(0.26)	(2.88)		(3.12)	(2.13)	(2.32)	(1.62)	(1.00)						

-statistics are in parentheses.

[a] $\hat{\delta}'$ is the coefficient estimate of $\log S_{dt-1} - \log S_{dt-13}$ under the non-perfect expectational hypothesis.

for industry 332 the estimate of the coefficient α_1' of the lagged dependent variable is not significant and of the wrong negative sign, and the estimate of the coefficient ρ_0' of the inventory variable is significant but of the wrong positive sign. For these three industries the same conclusion is reached here using Census data than was reached above using IRS, RMA, and Bureau of Mines data: the equation developed in this chapter gives better results than the HMMS equation. [Neither, of course, gives results as good as eq. (3.9)′.]

For industry 201 the HMMS equation in table 6.7 gives better results from the point of view of goodness of fit than either eq. (6.8)′ in table 6.6 or eq. (3.9)′ in table 6.5. In table 6.7, however, only one of the expected future changes in sales variable is significant for industry 201, and most of the explanatory power comes from the lagged dependent variable, although the coefficient estimate of the inventory variable is significant and of the right sign. The results for industry 201 using Census data are so much worse than the results achieved using FRB data that comparisons of the different equations using Census data are probably of little value.

6.7 Summary

The major conclusion of this chapter is that models such as the one developed in ch. 3 which specify a one-way causality from decisions on production to decisions on employment appear to be more realistic than models such as the one of HMMS or the one developed in this chapter which assume that production and employment decisions are made simultaneously. The HMMS model, which is based on the minimization of a short-run cost function and in which the level of sales rather than the level of production is assumed to be exogenous in the short run, yielded the worst results of the three models tested. This was not unexpected since the HMMS overtime cost approximation, which is depicted in figure 6.1, is likely to be quite unrealistic if firms do in fact hold positive amounts of excess labor during much of the year. The alternative model developed in this chapter, which combines the HMMS idea that production and employment decisions are made simultaneously with the idea of the model developed in ch. 3 that the amount of excess labor on hand should affect employment decisions, yielded better results than the HMMS model, but still not as good as the model developed in ch. 3: the expected future change in output variables were more significant in eq. (3.9)′ than the expected future change in sales variables were in eq. (6.8)′.

Some results were presented using Bureau of Census data which indicate that the Census data, which are in value terms, are not as good as the FRB and RMA data, which are based on physical quantities. Nevertheless, the results achieved using Census data were consistent with the results achieved using the other data in that eq. (3.9)′ gave better results than eq. (6.8)′ and, except for industry 201, eq. (6.8)′ gave better results than the HMMS equation (6.7)′.