Flexible Work Hours and Productivity: Some Evidence from the Pharmaceutical Industry

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Flexible work hours potentially influence productivity through effects on absenteeism and turnover, organizational attachment, job attitudes, work-related stress, and other areas. Prior studies suggest positive effects on productivity but are inconclusive because of small sample sizes, failure to apply direct productivity measures, or failure to account for other associated changes. We apply alternative fixed- and random-effects models to estimate production functions using panel data, with controls included for firm effects, time effects, capital quality, autocorrelation, and specification error. The results suggest that flexible work schedules contribute to improvements of about 10 percent in productivity.

Introduction

During the past decade there has been an increase in the use of flexible work schedules and other types of alternative work schedules, including part-time positions, work sharing, work-at-home, and family leave contingencies. Economic, sociological, and structural changes may account partly for these changes, including the growth in dual-income households, the increased participation of women in corporate management, and other possible factors. With the increase in dual-income households with children, workers require greater flexibility to meet the varying demands of

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family life. Companies, anxious to keep down costs while attracting top workers, may offer flexible work schedules (rather than higher wages) to attract and retain employees. Recent employer surveys have documented significant increases in the use of flexible work hours, or "flextime," with over 30 percent of firms offering some type of flexible work schedules, more than double the percentage just 15 years ago, according to a recent survey (Cregar 1988). Other recent surveys suggest that over 50 percent of larger companies have some form of flexible work hours (Christensen 1989; Galinsky, Friedman, and Hernandez 1991).

The potential effect of flexible work hours on productivity has not been comprehensively researched. Recent studies suggest there may be positive effects on absenteeism and turnover, organizational attachment, job attitudes, off-job satisfaction, and work-related stress (e.g., Pierce and Newstrom 1980, 1982). Other studies that apply direct measures of productivity (e.g., output per employee-hour) find positive effects in some cases and no measurable effects on productivity in others (Schein, Mauer, and Novak 1977; Kim and Campagna 1981). One study investigated performance in work units in two government agencies, one with flextime and one without, and found positive productivity effects where workers shared capital resources, and no effects where they did not (Ralston, Anthony, and Gustafson 1985).[1] Another study found positive effects on cooperation, and work-group and superior-subordinate relations for lower-level employees only (not the professionals or managers); however, the same study found no perceived effects on individual or group productivity (Narayanan and Nath 1982). Most of the research into this area has been performed within the behavioral and management sciences, and has involved detailed case studies to investigate changes in workers' and managers' attitudes and performance following adoption of flexible work schedules, compared with those of a control group, for work groups within one or a few firms.[2]

The results from these studies suggest there may be positive effects in some circumstances, but they are largely inconclusive because of relatively small sample sizes, failure to apply direct productivity measures, failure to use a pretest or a control group, or failure to account for structural or technological changes that may have produced the positive effects. Although numerous articles have appeared in business, management, and

[1] Computer programmers shared access to computers in this study, while keypunch operators had no similar limitation.

[2] For examples of studies on flexible working hours see the following: Dalton and Mesch 1990; Evans 1973; Golembieski and Proehl 1978; Hicks and Klimoski 1981; Mellor 1986; Nollen and Martin 1978; Orpin 1981; Owen 1977; and Schein, Mauer, and Novak 1977.

psychology journals highlighting successful cases and providing constructive information on plan design, to our knowledge no study has estimated an economic production function model to investigate the economic effects of flexible work schedules.

General Approach and Data Sources

To address these questions, we specify and estimate an economic production function model using firm-level panel data for a test industry, the pharmaceutical industry, in U.S. manufacturing. The econometric approach allows us to address two related issues: The first issue is whether companies with flexible work schedules exhibit higher levels of productivity than those without flextime. The second issue concerns the sensitivity of labor productivity to the degree of flexibility provided. Is the presence of flexible work schedules sufficient to bring about any potential increases in productivity, or is the degree of flexibility provided a significant factor? The first issue is addressed by including a binary flextime variable in the production function model; the second issue requires that a continuous specification for flextime be developed to measure the degree of flexibility provided. The production function model applying both specifications is developed more fully below.

The pharmaceutical industry was selected because it represented one of the largest homogeneous groupings of companies in manufacturing (at the four-digit SIC code level), where the financial data required for production function estimation were readily available. Other possible candidate industries in manufacturing either had insufficient financial data or represented more highly aggregated groupings of companies (i.e., at the two- or three-digit SIC code level). Alternative versions of the model, including fixed effects and random effects specifications, are estimated to control for firm effects on productivity, and standard approaches are applied to correct or control for autocorrelation, selection bias, and other factors that potentially explain the observed results such as vintage of capital, time effects, or varying rates of capacity utilization.

The primary data sources used in this study are the annual firm-level data available through the Industrial COMPUSTAT[3] (by Standard and Poors), combined with survey data on flexible work hours collected by the

[3] COMPUSTAT is a standardized firm-level database containing extensive information from financial reports on over 3,500 publicly traded companies in each business sector of the United States. COMPUSTAT provides measures for most of the economic variables needed for production function estimation; the standardization of the data across companies makes it well suited for economic studies using firm-level panel data.

Industrial Relations and Human Resource Management (IRHRM) Department at Le Moyne College. The initial list of companies included all 56 companies from the COMPUSTAT files with four-digit SIC code 2834. Of these 56 pharmaceutical companies listed in COMPUSTAT, only 50 had sufficient data to warrant inclusion in our sample. Of those 50 companies, 36 were willing to participate in our survey, representing a response rate of 72 percent. We collected information covering an 11-year period, from 1981 through 1991. The primary data on flexible work hours were collected by a telephone survey, with follow-up to nonrespondents, administered to human resource professionals at the respective companies. The data provided us with information on whether flextime was used by the organization and the years it was in use between 1981 and 1991. Of the 36 companies, only 21 had complete information over the 11-year period in COMPUSTAT. The other companies had at least five years of data, giving us an unbalanced panel data with 332 observations. The final step for creating the database was to merge the survey data with annual panel data available through COMPUSTAT.

Applying the continuous version of the model required that additional information on specific features of the flextime program be collected. A mail survey was sent to each of the companies identified previously as having a flextime program in operation.[4] The initial list of companies was the same and included all 56 companies from the COMPUSTAT files with four-digit SIC code 2834, with 50 companies having sufficient data to warrant inclusion in our sample. Of those 50 companies, 33 were willing to participate in our second survey, representing a response rate of 66 percent. We collected information covering an 11-year period, from 1981 through 1991. The data on flexible work hours were collected by questionnaire mailed to human resource professionals at the companies who had indicated from the previous telephone survey that their company had a flextime program. These data provided us with information on the core hours, the number of flexible hours, and the percent of employees eligible for flextime benefits. Of the 33 companies, only 21 had complete information over the 11-year period in COMPUSTAT. The other companies had at least five years of data, giving us an unbalanced panel data with 299 observations. The final step for creating the database required for the study was to merge the survey data with annual panel data available through COMPUSTAT. Because of a slightly smaller response rate, the data set for estimating continuous versions of the model was smaller than the one for estimating the binary version of the model.

[4] A copy of the mail survey is available from the authors upon request.

Theory and Specification

For the purposes of this article, flexible work hours or "flextime" is defined as a formal or informal arrangement between employers and their employees that allows the *employee* at least some discretion or control over the specific hours of the day or week when the work is to be performed. Typically, flextime programs have specific "core hours" when employees are required to be at work and additional hours that may be worked at the employees' discretion, provided the core plus the additional hours equals the agreed upon total. Under a flextime program, some workers may report to work at 6 A.M. and work until 2 P.M., whereas others may report at 12 noon and work until 8 P.M. To qualify as a flextime program, the worker must have some choice over which hours to work, and be allowed to adjust hours in response to contingencies or changing circumstances. It is important to define flexible work hours precisely because many companies have flexible scheduling that does not meet our criteria. For example, workers may have varying part- or full-time schedules within a company but no individual choice over which hours to work, except by quitting and taking a different job. On the other hand, some companies may provide for flexible work hours without a formal or written flextime program by allowing employees to work at home.

Although the theory underlying potential productivity effects has not been formally developed in the context of an economic model, there are several channels whereby flexible schedules might influence productivity, including:

- workers may increase effort, reduce shirking, work harder or work smarter, cooperate more fully in training, assisting, and monitoring other workers, or reduce absenteeism and turnover. Because employees should prefer working in companies with flextime, the costs of losing the job will be higher. The arguments here are similar to those made by efficiency wage theorists (for example, see Akerloff and Yellen 1986). In addition, with flextime, workers may choose to work during their peak hours, in terms of personal productivity.
- companies may attract better workers, even if individual levels of productivity are unaffected. Because workers will prefer flexible work schedules, companies with these arrangements may get larger applicant pools from which to choose the most productive workers.
- capital productivity may be enhanced (or adversely affected) by staggered work hours or more frequent shift changes. Capital productivity should be enhanced by using equipment for additional hours of a day;

however, it may be adversely affected by more frequent changing of personnel or entire shift changes. The effect on capital should depend on the nature of technology, as well as the importance of individual versus team production in producing the output of the firm.

- management efficiency may be reduced (or enhanced) because monitoring and supervisory costs may be higher (or lower) in companies with flexible work schedules. Because of staggered shifts or more frequent personnel changes, additional hours of monitoring may be required for some types of production activities. On the other hand, if the managers of the company also have flexible hours, the productivity of managers may increase for the same reasons cited above. The effect of flexible work schedules on management efficiency probably depends on the nature of the production process, the number of employees and managers, and the specific monitoring requirements. Many types of production activities do not require constant monitoring and control, and individual (as opposed to team) productivity may not be directly observable or measurable. Management efficiency may be enhanced if flexible arrangements allow the company to attract better managers or better workers who do not require as close supervision.

Because reasonable arguments can be constructed suggesting both positive and negative effects on productivity, the issue will likely be resolved through empirical investigations and carefully designed case studies.

Model Specification

Because flexible work schedules potentially influence a firm's level of productivity, an economic production function model is appropriate for testing and measuring potential effects. Based on the mechanisms by which flexible work hours might translate into improved performance, a factor augmentation model of production provides one method for measuring the impact of flexible work hours on productivity and for identifying the individual causal channels. Applying a simple Cobb-Douglas (C-D) production function model (modified to allow for productivity effects by incorporating a constructed flextime variable), it is possible to estimate the net effect of flexible work schedules on productivity. More general functional forms for production, such as the constant elasticity of substitution (CES) or the translog (T-L) production function, can be applied to relax restrictive assumptions about the firm's technology, or to identify and test for embodied effects. This general approach has been used in prior studies to estimate effects of unions, profit sharing, or employee ownership on productivity. (See Brown and Medoff 1978; Shepard 1994; and Kruse 1992.)

Estimating equations were developed under alternative functional forms for production including the C-D, CES, and the T-L production functions. Because the data did not support using the more flexible forms over the C-D production function, we present only the C-D model and corresponding estimates here. The C-D function is highly restrictive, however, and imposes the condition that the elasticity of substitution among factors of production be equal to one. More general forms such as the CES or the T-L are less restrictive and potentially allow for the identification of effects on productivity that are embodied in individual factors of production. Unfortunately, the data were too limited to provide sharp estimates of the effort parameters that represent the embodied effects. The statistical tests for using the CES or the T-L over the C-D were rejected. Therefore we focus on estimating the net effect of flexible work hours on productivity applying the C-D model; identifying the individual causal channels remains an important extension.

First, we consider alternative specifications for a flextime variable; following this we show how this variable can be incorporated into a general production function model. Alternative binary or continuous specifications for the flextime variable (F) can be used to measure potential productivity effects. The simplest is to assume that the variable F is represented by an exogenous binary variable, taking a value of one if the firm has flexible work schedules, and 0 otherwise. This is the appropriate specification if the mere presence of flexible work plan is the important factor, rather than the "level" or degree of flexibility measured in some way. On the other hand, potential effects of flexible work schedules may depend on the degree or extent of flexibility provided. For this article, we apply both binary and continuous specifications for the flextime variable. The continuous specification is appropriate if potential effects of flexible work schedules depend on the degree or extent of flexibility provided. The continuous measure of flexible work schedules that is applied is the following:

$$F = (1 - C/H) \cdot \mathrm{P} \cdot 100, \qquad (1)$$

where

F = continuous measure of flexibility provided to workers

C = number of "core" hours when workers are required to be at work during a given time period

H = total number of hours during the time period in which workers may perform the work (e.g., the number of hours the office or plant is open)

P = proportion of workers covered by the flexible work plan (employee coverage).

Complete flexibility provided to workers (i.e., 0 "core" hours) implies that $F = 100$, assuming full coverage. If there is no flexibility (i.e., fixed work schedules), then the values for F will equal 0 because $C = H$.

With factor augmentation, factors of production are redefined in terms of efficiency units, with factor effort functions entering multiplicatively alongside factor arguments in the production function. The potential effect of the flextime variable on productivity is not restricted a priori to be positive, neutral, or negative; the properties of the effort functions are sufficiently general to allow for each of these possibilities. Let

a) $E(F)$ = labor effort function, and (2)
b) $E(F) \cdot L$ = number of labor efficiency units.

If the overall effect of flexible work schedules on productivity and the effort response to the changes in the flextime variable are non-negative, we have $E(F) \geqslant 1$ and $dE/dF \geqslant 0$; $F \geqslant 0$. If the overall effect is negative, the signs of the above inequalities are reversed, although $E(F)$ must still be $\geqslant 0$ to assure non-negative marginal products. With F measured as a binary variable, the derivatives will be undefined. With the specification presented below, $E(F) = 1$ if $F = 0$, so that it reduces to the standard model for companies without flexible work schedules. Empirical estimates of $E(F)$ provide a method for testing whether flexible work schedules have positive or negative effects on productivity.

Applying a two-factor model, firms are assumed to hire or rent labor (L) and acquire capital (K) as factors of production in producing the final product (Q). Because the treatment of each factor in the production function model is symmetrical, it is straightforward to extend the analysis to include additional factors; we simplify the derivation by presenting a two-factor model (labor and capital) and omitting firm and time subscripts. The multifactor model provides a framework in which to identify the individual causal channels whereby flexible work schedules may be effective. The productivity of each factor may be influenced through interactions with labor, and so an effort function must be specified for each factor even though labor may be the only factor directly covered by the plan. Hence:

a) $G(F)$ = Capital effort function (3)
b) $G(F) \cdot K$ = Number of capital efficiency units.

The "effort" functions are assumed to be of the following form:

a) $E(F) = (1 + a_l)^F$; $F \geqslant 0$; $-1 \leqslant a_j \leqslant 1$; $j = l,k$ (4)
b) $G(F) = (1 + a_k)^F$ F measured as binary

or

c) $E(F) = (1 + a_l)^{\ln(F+1)}$; $F \geq 0$; $-1 \leq a_j \leq 1$; $j = l,k$
d) $G(F) = (1 + a_k)^{\ln(F+1)}$ F measured as continuous.

The parameters a_l and a_k are the effort parameters for labor and capital effort functions, respectively. These represent the labor and capital channels whereby flexible work schedules may be effective. The signs of a_l and a_k indicate the direction of the effect of flexible work schedules on productivity via these channels, with values greater than 0 implying a positive effect on labor or capital productivity. This is a convenient form for estimation because it reduces to the standard model with $E(F) = 1$ if $F = 0$ or if $a_j = 0$.[5] Thus factor augmentation is incorporated into the model without imposing it, and the effect of flexible work schedules on worker "effort" depends on the signs of the individual effort parameters.

To derive the estimating equations, firms are assumed to employ labor (L) and capital (K) in producing output (Q). With C-D technology, the production function for a representative firm may be written as:

$$\begin{aligned} &\text{a) } Q = A[(1 + a_l)^F \cdot L]^\alpha[(1 + a_k)^F \cdot K]^\beta e^u;\ F \text{ measured as binary, or} \\ &\text{b) } Q = A[(1 + a_l)^{\ln(F+1)} \cdot L]^\alpha[(1 + a_k)^{\ln(F+1)} \cdot K]^\beta e^u;\ F \text{ measured as continuous.} \end{aligned} \tag{5}$$

To transform the left side of the equation into a direct productivity measure, we divide by L and transform the equation into its intensive form. This form is consistent with prior labor productivity studies and is convenient for empirical estimation. Taking logs and making use of an approximation, the following estimating equation is obtained:

$$\begin{aligned} &\text{a) } \ln(Q/L) = \ln A + (\alpha a_l + \beta a_k)F + \beta\ln(K/L) + (\Theta - 1)\ln L + u \\ &\qquad \text{or} \\ &\text{b) } \ln(Q/L) = \ln A + (\alpha a_l + \beta a_k)\ln(F + 1) + \beta\ln(K/L) + (\Theta - 1)\ln L + u, \end{aligned} \tag{6}$$

[5] Using this form, it can be shown that the following conditions will hold:

a) $E(F) = 1$; if $F = 0$; $-1 < a_j \leq 1$
b) $E(F) \geq 0$; $F \geq 0$; $-1 < a_j \leq 1$
c) $E(F) = 1$; if $a_j = 0$; $F \geq 0$.

With the binary specification for the flextime variable, the derivative of the effort function with respect to F will be undefined. With continuous specifications for the flextime variable, we specify the effort function in the form of $E(F) = (1 + a_l)^{\ln(F+1)}$. The effort function will then exhibit diminishing returns and the following conditions will also hold:

d) $\partial E(F)/\partial F \geq 0$; $F \geq 0$; $a_j \geq 0$
e) $\dfrac{\partial E^2(F)}{\partial F^2} \leq 0$; if $F \geq 0$; $a_j \geq 0$.

where the error term represents random deviations from technical efficiency by the individual firm, and Θ is a measure of returns to scale (i.e., $\alpha + \beta$). Output per worker depends on the capital/labor ratio, scale of output, and the flextime variable F. Note that $(\alpha a_l + \beta a_k)$ provides a measure of the net effect of flexible work schedules on productivity. With the binary case, it represents the percentage change in output per worker following implementation of flexible work plans. With the continuous case, note that $(\alpha a_l + \beta a_k)$ provides a measure of the elasticity of labor productivity with respect to the constructed flextime variable. If flexible work schedules also increase managerial efficiency, that effect would become part of this term as well.[6] Note that although the net effect of flexible work hours on productivity is identified with the C-D model, the individual effort parameters are not. The C-D model therefore reduces to the same model applied in other studies, where the effects of some organizational factor are allowed to enter through the constant term rather than by augmenting individual factors of production (e.g., Brown and Medoff 1978). When more general functional forms are used to characterize production, however, the factor augmentation model allows for identification of embodied effects.

Equations (6a) and (6b) represent the basic equations to be estimated applying alternative estimation techniques described in the following section. The production function model can be readily modified to include control variables for such factors as vintage of capital, rate of utilization, or technical change, among other possible variables, applying approaches commonly used in other studies.

Empirical Models and Results

The estimation of equations (6a) and (6b) is accomplished using panel data. While ordinary least-squares (OLS) can be used if certain conditions are satisfied, the estimation is complicated by several factors. One problem is the possible endogeneity of either the flextime variable or the factors of production. Zellner, Kmenta, and Dreze (1966) have demonstrated that OLS is a reasonable approach for estimating production functions

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[6] The constant term A can be interpreted as an index of organizational efficiency. One method for investigating effects of flexible work schedules on managerial efficiency is to measure effects on the constant term A. Let $A^* = A(1 + d)$, where d represents the percentage change in productivity following the flexible work hours due to organizational factors. The log of the above, for small changes in d that are close to 0, can be expressed as: $\ln A^* = \ln A + \ln(1 + d) = \ln A + d$. The net effect of flextime on productivity is therefore $(\alpha a + \beta b + d)$, where αa represents the labor channel, βb the capital channel, and d the effect through changes in organizational efficiency.

(see also Hildebrand and Liu 1965; and Griliches 1967). Two-stage least-squares (2SLS) can be estimated with the continuous flextime variable to determine if any significant bias is due to endogeneity.

The usual panel data models, including the fixed effects and random effects models, are estimated and tested for appropriateness. The fixed effects models can be used to eliminate individual firm effects that would otherwise bias the estimated coefficients. The fixed effects models used in these estimations are the least-squares dummy variable (LSDV) model, with the fixed firm effects accounted for by including individual company intercept terms (see Greene 1990). There is sufficient variation in the flextime variable over time and across firms to allow for estimation of the fixed effects model as well as the random effects model. A Hausman (1978) specification test is used to determine the appropriateness of the random effects model in comparison to the fixed effects estimates. Large values indicate rejecting the random effects model in favor of the fixed effects model. The LSDV estimates are consistent but are generally not efficient; therefore the estimated random effects models are preferred provided the random effects are orthogonal to the regressors.[7]

Table 1 provides the means and standard deviations of the variables used in the analysis with their simple correlations. Measurement of output per worker used is net sales in millions of dollars divided by the number of employees. Construction of a measure of value added was not possible due to the lack of information for most companies on their labor cost. Measurement of labor is in number of employees and the measure of capital is gross plant value in millions of dollars.[8] Simple correlations show the use of flextime to be associated in general with larger firms and to have increased in use over time. With the estimates applying the binary measure for the flextime variable, 14 of the 36 companies used flextime with 7 of those using it over the entire 11-year period. With the estimates applying the continuous measure, 11 of the 33 companies used flextime with 7 of those using it over the entire 11-year period. None of the companies from either sample discontinued their flextime programs; the changes over time in use of flexible work hours resulted from the implementation of flextime programs by several companies at some point during the study period. Other additional independent variables used for controls include capital quality measured as the ratio of net plant value to gross plant value, and a simple

[7] Large values of the Hausman test reject the notion that the individual effects are uncorrelated with the regressors, and hence the random effects model is inappropriate.

[8] Labor is measured as number of employees (in thousands) because data on worker-hours are unavailable.

TABLE 1

DESCRIPTIVE STATISTICS AND CORRELATIONS

			Correlations				
Variable	Mean	Sd.	1	2	3	4	5
Net Sales/Employee	114.9	52.3					
Gross Plant/Employee	55.6	33.6	.45				
Employees	15.3	20.2	−.09	−.00			
Flextime (binary)	.289	.454	.11	.35	.37		
Flextime* (continuous)	5.73	13.7	.09	.18	.32	.81	
Time	6.43	3.1	.47	.47	−.04	.14	.18

Notes: Net sales, gross plant are in millions of dollars, employees are in thousands.
* N = 332 except for flextime continuous variable when N = 299.

log-linear time trend.[9] A lagged value of the log of research and development cost was also tried; it was not significant in any of the preferred models and had no effect on the variables of interest.[10] It was dropped to increase sample size.

As indicated by Equations 6a and b, the log-intensive form of the production function is the equation to be estimated applying alternative fixed effects and random effects specification. Alternative binary and continuous specifications for the flextime variable are used in the estimation. Estimates from the preferred models are presented in Table 1.[11] The Hausman (1978) test suggests that we cannot reject the random effects model in favor of the fixed effects model. If autocorrelation is present, the estimated coefficients would be unbiased but inefficient. The estimates presented, controlling for autocorrelation, assume a common value of rho. Given our relatively short time period, this restriction is not likely to be harmful and may actually improve the small sample properties of the estimated coefficients (see Greene 1990).

[9] Time dummies were also tried, but the results of the estimations were not sensitive to the choice of time effects. Estimates were also tried using firm-specific time trends, but with no effect on the flextime variable estimates or significance. Estimates presented use the simpler form which increases the degrees of freedom. For some sets of estimates a rate of utilization variable was included, calculated as the ratio of actual to potential output for each firm. Potential output was estimated using peak output values within the time series for each firm. Including the rate-of-utilization variable made no difference in the resulting estimates and turned out to be insignificant. It is therefore not included with the estimates presented in Table 1.

[10] One referee pointed out that research and development (R & D) expenditures might be associated with use of flexible work schedules, and that this could explain part of any measured effects on productivity. The use of lagged levels for R & D expenditures is consistent with recent studies (for example, see Nadiri and Mamuneas 1994).

[11] The nominal values were used in the estimations presented. Deflating of the output and gross plant value made no difference in the estimated parameters.

TABLE 2

PRODUCTION FUNCTION ESTIMATES, COBB-DOUGLAS TECHNOLOGY

Dependent Variable = log(net $sales_{it}/labor_{it}$)

Independent Variables[a]	Random Effects	Random Effects	2SLS[b] Fixed Effects
Const	3.567***	3.825***	(no constant)
	(.249)	(.297)	(group dummies)
Log(L)	−.009	−.030	−.043
	(.020)	(.022)	(.031)
Log(K/L)	.322***	.364***	.428***
	(.063)	(.068)	(.078)
Flex Binary	.097*		
	(.052)		
Continuous		.038**	.063**
		(.016)	(.025)
rho	.20	.20	.30
R^2	.32	.31	.85
N	296	266	208

(standard errors in parentheses)
[a] additional variables—time trend and capital quality variable
[b] Two stage least squares
Significance level two-tailed test: *** = .01, ** = .05, * = .10

Table 2 provides the estimates from the preferred model, the random effects model. The fixed effects results are not presented here but were almost identical to those obtained with the random effects models. The basic outcome of the random effects model with the flextime binary variable shows that the hypothesis of constant returns to scale cannot be rejected. Estimates of the production parameters indicate an α equal to .67 and for β of .32. Most important for our purposes, the estimated coefficient of the flextime variable suggests an increase in productivity of approximately 10 percent for those adopting flextime. Although the significance is reduced when controlling for autocorrelation (p-value equals .07 for the two-tailed test), it still suggests a positive effect of flexible work hours on productivity.

The Cobb-Douglas production function estimate applying the continuous specification for the flextime variable is also presented in Table 2. The estimate presented is the random effects model using unbalanced panel data controlling for autocorrelation. As with the binary models, the Hausman tests were used to determine the appropriateness of the random effects models. The flextime variable is significant and provides an estimate of the elasticity of output per worker with respect to the constructed flextime variable of roughly .038. The estimates appear to be reasonable giving values of α of .67 and values of β of .36, indicating approximately constant returns to scale.

The estimates applying the continuous specification are also subject to possible selection bias; the continuous model was therefore estimated using two-stage least-squares with the flextime variable being treated as endogenous.[12] The results are shown in the final column of Table 2. There are no major changes in the results with the flextime variables still significant and showing an elasticity of .063.[13] This further suggests that the results are not dependent on the type of firm adopting flextime, but that the increased productivity results directly from the flextime program. Heckman (1990) has shown that instrumental variables can produce consistent estimates of the endogenous variable, as long as there are no unobserved components that contribute significantly to the endogeneity of the variable. In such cases, the instrumental variable approach would not differ from alternative self-selection correction approaches described in Heckman (1990).

Concluding Remarks

The findings from this study suggest that flexible work hours can contribute to improvements in productivity. The results were found to be generally insensitive to choice of estimation technique and to the inclusion of a variety of control variables in the model. The estimates applying the continuous measures for the flextime variable suggest that the degree of flexibility is a significant factor influencing productivity. However, given the exploratory and preliminary nature of this research, with the application of the model to a limited number of firms within a single industry, it is not clear whether the results are generalizable to other firms in other industries; more studies using different data sets and alternative model specifications are clearly needed.

One potential problem with the estimates presented in this article is the absence of controls for other human resource practices; it is possible that the flextime variable is serving as a proxy for other dimensions of human resource policies that could not be accounted for in the models. If this is so, the estimated productivity effects (or some of them) may be due to other unmea-

[12] Only the fixed effects models are estimated for the 2SLS because the properties of these estimates are known. The instruments for the estimates are the exogenous variables from the prior equations, the lag of the labor and capital variables, and the lag of the flextime variable.

[13] The binary value was also treated as an endogenous variable following Heckman (1978), using a linear probability model. The results were significant, suggesting a 24 percent effect of the use of flextime on productivity.

sured features of human resource practices that are correlated with the use of flextime. Unfortunately, data are currently unavailable to address this issue. To obtain comprehensive multidimensional data on each company's human resource policies would require an in-depth case study and evaluation of each company. The required sample size for estimating the production function models (with additional control variables representing human resource practices) would also significantly increase. A second potential problem concerns the use of "number of employees," instead of "labor hours," as the independent variable for labor in the regression equations. It is possible that use of flexible work hours is associated with changes in average hours worked, or with the distribution of full- and part-time workers within the firm. If, for example, flexible work schedules result in a movement from part-time to full-time work (with increases in average hours per worker), then our estimates would be biased upward and could indicate positive productivity effects even if the worker's productivity (per hour) is unaffected. Unfortunately, no hours data were available in order to test a preferred model using hours instead of number of employees. For our estimates to be unbiased, we must assume that hours worked, on average, are not influenced by the choice of flexible work hours, and that any changes in the distribution of full- and part-time workers (resulting from flexible work hours) have no corresponding effects on productivity.

It was also not possible, given the lack of data on absenteeism, to distinguish between productivity effects due to increased effort (or individual productivity) of workers, or due to reduced absenteeism. This remains an important extension for future research. The factor augmentation model, however, provides a promising approach for testing for embodied effects on labor, management, and capital productivity. The estimated coefficients of the factor effort functions provide evidence on which, if any, of the channels explains estimated effects on productivity. Identifying the individual causal channels, however, requires using more flexible functional forms for production such as the CES or the T-L. In addition, as part of future research, interactions between the flextime variable and other factors such as firm size, capital intensity, or other firm characteristics might be investigated to identify the settings where flextime is most effective. We are currently gathering additional data that may allow us to address some of these issues.

Finally, the findings from this research can provide input into a public policy evaluation of flexible work hours. Would society be better off if flexible work schedules were encouraged by public authorities, either through formal incentives such as tax breaks, or informally through dissemination of information and other means of encouragement? Societal benefits are potentially greater in scope than the private benefits and include, for example, reduced traffic congestion and improvements in child care. Potential externalities need to be evaluated to determine appropriate public policy. If the external effects are significant, it is possible that flexible work schedules should be encouraged even if corresponding productivity effects are 0. Our results provide useful information for evaluating these important public policy questions.

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