



Hearts and Minds: A Social Model of U.S. Productivity Growth

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Hearts and Minds: A Social Model of U.S. Productivity Growth

After ten years of continuing immersion in the whole productivity analysis and debate, what comes through loud and clear is that there are some things that are common to all circumstances of high levels of performance. . . . These are matters of the heart and mind and not of hardware and capital.—Hallett¹

MOST ECONOMISTS agree that the slowdown in aggregate productivity growth in the United States since the mid-1960s has played a pivotal role in the poor performance of the U.S. economy. And yet, “despite numerous studies of the slowdown,” *BPEA* editors William C. Brainard

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1. Jeffrey J. Hallett, “Productivity—From the Bottom Up,” in Robert Friedman and William Schweke, eds., *Expanding the Opportunity to Produce: Revitalizing the American Economy through New Enterprise Development* (Washington, D.C.: The Corporation for Enterprise Development, 1981), p. 406.

and George L. Perry conclude, “its causes have remained largely a mystery.”²

We think that this mystery stems more from the limitations of conventional economic analysis than from the impenetrability of slower productivity growth. Prevailing economic analysis typically neglects the human dimensions of production and the institutional contexts within which economic actors operate. We develop in this paper an alternative account of the productivity slowdown that addresses these various lacunae.

We argue in particular that declining work intensity and lagging business innovation since the 1960s—factors that have been almost entirely elided in recent analyses—provide crucial missing clues to the productivity mystery. To develop this argument we present and econometrically test a “social” model of aggregate productivity growth. It integrates technical and social dimensions of production and builds upon an analysis of the social setting that has conditioned productivity growth in the United States in the postwar period.³ It can account empirically for almost all the productivity slowdown. Our analysis is provisional; it raises many issues for further research, but we believe that it provides a promising foundation for resolving the puzzle of slower productivity growth in the U.S. economy.

We present an alternative account of the productivity slowdown in five parts. Some simple “stylized facts” related to work intensity and business innovation are first summarized. We then outline the basic elements of a social model of aggregate productivity growth. A detailed econometric test of that model is next presented, providing a comparison of its explanatory power with that of more conventional approaches. We then evaluate several possible additional or alternative hypotheses about the productivity slowdown, showing that the basic results of the paper are robust even when confronted with competing or supplementary interpretations. The paper concludes with a brief discussion of the policy implications that might be drawn from our explanation of the productivity puzzle.

2. William C. Brainard and George L. Perry, *BPEA*, 1:1981, p. vii.

3. This paper draws heavily on the historical and structural analysis developed in Samuel Bowles, David M. Gordon, and Thomas E. Weisskopf, *Beyond the Waste Land: A Democratic Alternative to Economic Decline* (Anchor-Doubleday, 1983), especially chaps. 4–5.

Declining Work Intensity and Lagging Business Innovation

Most economists have concentrated on two principal explanations of the slowdown in the rate of productivity growth—the oil-price shock and slower rates of capital formation. But these two explanations have two important flaws: first, neither factor took effect until 1973–74, well after the beginning of the productivity slowdown in the mid-1960s; and second, even after 1973, these two factors appear to account for a relatively small portion of the retardation in productivity growth.

Journalists, business observers, and historians frequently argue that two other serious problems began to afflict the U.S. economy after the mid-1960s: friction began to mount at the workplace, leading to an erosion of worker cooperation and worker effort; and corporations turned increasingly toward shorter-term investment policies, resulting in more sluggish business attempts to improve productive efficiency.⁴

These trends, if manifest, would obviously help explain the slowdown in productivity growth since the mid-1960s. But economists have tended to overlook these developments either because they do not typically study work intensity and business innovation in macroeconomic analyses of aggregate productivity growth or because they suspect that such qualitative factors cannot easily be integrated into rigorous quantitative investigation.⁵

4. See, among many such recent commentaries, The Business Week Team, *The Reindustrialization of America* (McGraw-Hill, 1982); James O'Toole, *Making America Work: Productivity and Responsibility* (Continuum, 1981); and Ira C. Magaziner and Robert B. Reich, *Minding America's Business: The Decline and Rise of the American Economy* (Harcourt, Brace, Jovanovich, 1982).

5. These qualitative factors are the intangibles about which C. Jackson Grayson writes in "Emphasizing Capital Investment Is a Mistake," *Wall Street Journal*, October 11, 1982: Concentration on capital investment has led to the relative neglect of "other factors" important for growth—management, quality, technology, knowledge, employee involvement, training and labor-management cooperation.

Why? For one thing, these other factors are mostly intangibles. Econometric models need numbers, and intangibles are difficult to measure and quantify. Also, . . . [it] is much more comfortable to work with things you can see, touch and kick. For both reasons, these intangibles are most often omitted from models, policies and managerial decisions, even though collectively they have a larger impact. As these other factors have increased in importance, their omission partly explains why our economic policies and forecasts have become increasingly inaccurate, and why our productivity slowdown has been so "puzzling" to many.

It is impossible, indeed, to measure directly or exactly either work intensity or innovative activity; one can neither attach ergometers to workers in the shop and office nor track the frequency of creative breakthroughs in corporate boardrooms and research laboratories. But we think there is sufficiently compelling indirect evidence of declining work intensity and lagging business innovation in the U.S. economy since the mid-1960s to warrant careful and systematic integration of these factors into analyses of the productivity slowdown in the United States.⁶

WORKPLACE FRICTION

From World War II through the early 1960s labor-management relations appear to have become increasingly peaceful and cooperative. By 1947, 90 percent of union contracts already pledged no strikes during the term of contract. Strike activity itself declined substantially; the proportion of work time idled because of strikes fell, for example, from an average of 0.54 percent in the first postwar business cycle, 1946–48, to 0.22 percent in the next four cycles, 1948–66. Although the early data are somewhat fragmentary, it appears that the proportion of workers satisfied with their jobs also increased significantly from the early 1950s through the mid-1960s.⁷

6. In all discussion that follows, we date business cycles by choosing as peaks the years in which the ratio of actual to potential GNP, as calculated by the Bureau of Economic Analysis and revised by the Council of Economic Advisers, reached its business-cycle peak. When comparing business-cycle averages, we date the cycles in the text and tables as extending from one peak to the next even though most of the cycle averages are calculated for the years extending from the year after the peak to the following peak.

7. The union no-strike contract figure is from Fred H. Joiner, "Developments in Union Agreements," in Colston E. Warne and others, eds., *Yearbook of American Labor*, vol. 2, *Labor in Postwar America* (Remsen Press, 1949), p. 35. Strike frequency in this and subsequent paragraphs is from U.S. Department of Labor, *Employment and Training Report of the President, 1981* (Government Printing Office, 1981), table G-8. Data on trends in work dissatisfaction summarize results of a question asked consistently since the mid-1950s by the Opinion Research Corporation: "How do you like your job—the kind of work you do?" We summed the percentages responding "very much" or "a good deal." Although the data are confidential, they are summarized in Michael R. Cooper and others, "Early Warning Signals: Growing Discontent among Managers," *Business*, January–February 1980. For data on job satisfaction reported in subsequent paragraphs, dates reported in the text correspond to the particular periods of aggregation reported in this last article.

Real and obvious benefits to production workers during the postwar boom led to this harmony. Real spendable hourly earnings increased at an average annual rate of 2.1 percent from 1948 to 1966; and the incidence of industrial accidents—one obvious barometer of working conditions—declined by almost one-third from its average during the first cycle of the postwar boom, 1946–48, to its average during the last cycle, 1959–66.⁸

After 1965 this rosy glow began to fade. During the next business cycle from 1966 to 1973, for example, the average annual growth of real spendable hourly earnings fell to 1.0 percent, and the average frequency of industrial accidents increased by 24 percent over its average for the previous cycle.

At the same time, tight labor markets increased workers' relative bargaining power and moderated the risks of dismissal. During the 1966–73 cycle, for example, the average ratio of quits to layoffs in manufacturing almost doubled its average in the previous cycle, reflecting the greater sense of labor independence that the late-1960s boom had engendered.⁹

Taking advantage of this heightened relative independence, workers appear to have become increasingly restive at the workplace and in their relationships with employers. The incidence of part-time absenteeism increased by 32 percent from 1959–66 to 1966–73. The average annual percentage of work time lost to strikes increased by 115 percent from 1959–66 to 1966–71 before the Nixon wage-price controls moderated the surge in 1972–73. From 1961–67 to 1967–73, further, the percent of strikes because of working conditions increased by more than one-third, and the percent of strikes taking place during the term of contract, more familiarly known as wildcat strikes, increased by one-fourth.¹⁰

8. Because of serious problems with the traditional Bureau of Labor Statistics series on real spendable weekly earnings, we developed our own alternative series on "real spendable hourly earnings." See Thomas E. Weisskopf, "A New Spendable Earnings Series," Technical Note 2 (Economics Institute of the Center for Democratic Alternatives, October 1983). We similarly resolved problems in comparing accident rates from before and after new reporting practices were instituted in 1970. See Michele I. Naples and David M. Gordon, "The Industrial Accident Rate: Creating a Consistent Time Series," Technical Note 1 (Economics Institute of the Center for Democratic Alternatives, December 1981).

9. Quits and layoffs here and in subsequent paragraphs are from *Employment and Training Report of the President, 1981*, table C-14.

10. Data on absenteeism, strikes to improve working conditions, and wildcat strikes are from Michele I. Naples, "The Structure of Industrial Relations, Labor Militance, and

This spreading worker restiveness does not appear to have been limited to blue-collar workers or workers in unions. Among all production personnel, both blue-collar and white-collar employees, job satisfaction declined between 1965–69 and 1970–74. According to detailed data available from the University of Michigan's Quality of Work Life Surveys beginning in 1969, this declining job satisfaction was surprisingly widespread; it affected white-collar, professional, technical, and managerial workers as well as those in blue-collar occupations.¹¹

After 1973, of course, labor markets loosened and—by conventional expectations—workers' sense of independence was bound to decline. (The average ratio of quits to layoffs indeed declined, although only slightly, from 1966–73 to 1973–79.) But the restiveness apparently persisted, despite rising unemployment, and in many cases appears to have continued spreading. Absenteeism rates did not decline in 1973–79 from the average of the previous cycle, while both the percentage of strikes over working conditions and the percentage of wildcat strikes increased.

Perhaps because workers were still discontented but increasingly fearful about either job quits or protests through strike activity, they appear to have become increasingly alienated on the job after 1973. The

the Rate of Growth of Productivity: The Case of U.S. Mining and Manufacturing, 1953–1977" (Ph.D. dissertation, University of Massachusetts at Amherst, 1982), tables 24 and 4. Dates in the text for 1961–66 are determined by 1961 starting points on all three data series.

We concentrate in the text on aggregate indicators of trends in work intensity because the focus in this paper is on the slowdown in aggregate productivity growth. We recognize, nonetheless, that such aggregative indicators are subject to a wide variety of distortions and that disaggregated industry studies are necessary to provide more substantial support for our hypotheses about lagging work intensity. The two most rigorous industry studies of which we are aware, one on coal and one on automobiles, provide strong support not only for our inferences about the timing and magnitude of trends in work intensity after the mid-1960s but also for our hypotheses about the links between these developments and the industry-specific slowdowns in productivity growth. On the coal industry see M. Connerton, R. B. Freeman, and J. L. Medoff, "Productivity and Industrial Relations: The Case of U.S. Bituminous Coal" (Harvard University, Department of Economics, December 1979). On the automobile industry see J. R. Norsworthy and C. A. Zabala, "Worker Attitudes and the Cost of Production," paper prepared for the National Bureau of Economic Research Workshop on Investment and Productivity, July 1983. On manufacturing as a whole see Michele I. Naples, "The Structure of Industrial Relations, Labor Militance, and the Rate of Growth of Productivity."

11. See the sequence of surveys, *Quality of Work Life* (Institute for Social Research, University of Michigan), for 1969, 1973, and 1977.

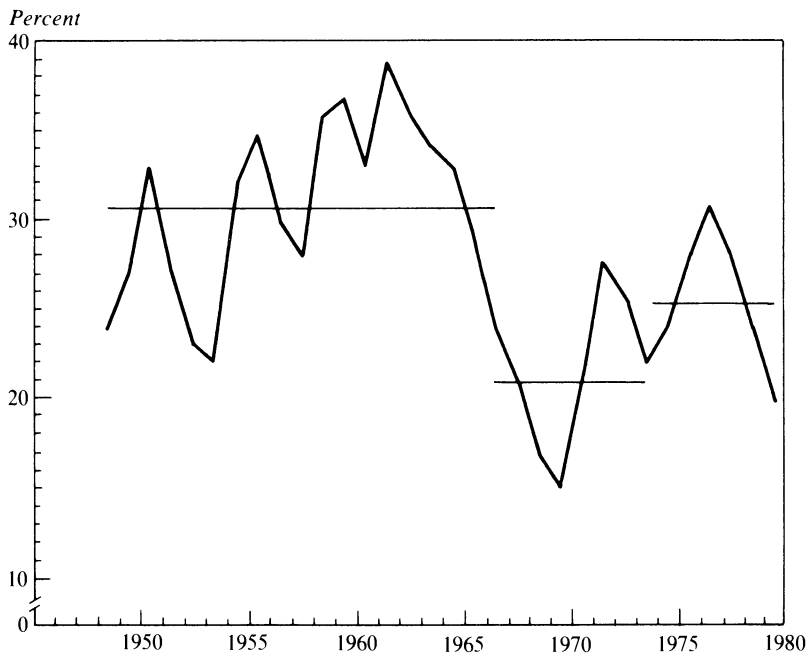
percent of nonsupervisory workers satisfied with their jobs, according to the longest continuous survey available, fell from 68 percent in 1970–74 to 59 percent in 1977–79, triple the rate of decline from 1965–69 to 1970–74. And the pervasiveness of job dissatisfaction became increasingly apparent. Graham Staines concluded from the detailed data available in the Michigan surveys from 1973 to 1977: “The sky had finally fallen. Workers in virtually all occupational and demographic categories evidenced appreciable . . . [and] unmistakable manifestations of rising discontent.”¹²

How can all this evidence be summarized? We think that much of it can be illuminated through a simple proposition that we develop more formally in subsequent sections: the higher is the cost to workers of losing their jobs, the more cooperative they are likely to be at the workplace. The lower is the cost of losing their jobs, in contrast, the less responsive they will be to employer efforts to boost productivity and extract greater labor effort. We present in figure 1 a summary measure of the “cost of job loss,” defined as the average annual percentage of an employee’s living standard that a representative worker could expect to lose if dismissed (see the text below for further discussion of this variable). Superimposed on the annual series are the period averages for 1948–66, 1966–73, and 1973–79. Disregarding for the moment cyclical movements, the cost of job loss rose until the early 1960s and then fell precipitously until the early 1970s; despite much higher unemployment rates after 1973, the cost of job loss did not return to anything close to its levels during the postwar boom.

Based on this schematic and necessarily indirect evidence, we hypothesize that workers became less fearful of losing their jobs after the mid-1960s, that they became increasingly restless at the workplace, and that their labor effort might well have declined as a result. Economists may have been slow to recognize these trends, but business observers noticed them early. The *Wall Street Journal* reported in 1970, for example:

Observers of the labor-management scene . . . almost unanimously assert that the present situation is the worst within memory. . . . Morale in many operations

12. Graham L. Staines, “Is Worker Dissatisfaction Rising?” *Challenge*, vol. 22 (May–June 1979), p. 39. See also Graham L. Staines and Robert P. Quinn, “American Workers Evaluate the Quality of Their Jobs,” *Monthly Labor Review*, vol. 102 (January 1979), pp. 3–12.

Figure 1. The Cost of Job Loss, 1948–79^a

Sources: Text equation 6 and the data cited in the appendix.

a. The variable is defined as the average annual percentage of an employee's living standard that a representative employee could expect to lose if that employee were dismissed from the job; the variable, expressed as a fraction, has a potential range from zero to 1.0. The horizontal lines in the figure represent averages of annual data for 1948–66, 1966–73, and 1973–79, respectively.

is sagging badly, intentional work slowdowns are cropping up more frequently and absenteeism is soaring. . . . [Many corporations] contend the problem . . . is so widespread it's their major headache at the moment.¹³

MANAGEMENT TORPOR

It has become almost commonplace among business observers, as *Business Week* puts it, that U.S. corporations have recently suffered “from a refusal to see beyond the next quarterly earnings statement.”¹⁴ Many suggest that corporations have been pursuing productivity-enhancing innovations less vigorously, shifting toward more speculative financial investments and shrinking from the longer-term entrepreneurial risks that provide a dynamic impulse in a growing economy.

13. Quoted in Jeremy Brecher, *Strike!* (Straight Arrow Books, 1972), pp. 266–67.

14. The Business Week Team, *The Reindustrialization of America*, p. 48.

These alarms may be overblown, but there may nonetheless be some useful kernels among the journalistic chaff. We think it quite likely, on the basis of available and largely indirect quantitative evidence, that U.S. corporations grew less and less inclined to introduce productive innovations after the mid-1960s.

First, applications for patents grew more slowly as the boom turned to stagflation. We can compare the average annual rates of growth in patent applications filed for inventions in successive five-year periods from the mid-1950s: 1956–60 to 1961–65, 2.5 percent; 1961–65 to 1966–70, 1.8 percent; 1966–70 to 1971–75, 1.4 percent; and 1971–75 to 1976–80, –0.1 percent.¹⁵

Second, by most available interpretations, the growth of private and public expenditures on research and development decelerated after the late 1960s. According to both Kendrick and Griliches, for example, it seems likely that the growth of R&D expenditures slowed during the 1966–73 business cycle and then slowed further or perhaps even stagnated after 1973.¹⁶

Third, one can observe a trend after the 1960s toward greater relative use of corporate funds for increases in financial assets—rather than for real investment and, therefore, for support or application of productive innovations. Increases in financial assets, as a percentage of all corporate uses of funds, rose from an annual average of 19.8 percent in 1959–66 to 25.4 percent in 1966–73 and to 25.8 percent in 1973–79.¹⁷

As we argue in the following sections, innovative pressure on business is best captured, other things being equal, by changes in the frequency of business failures. Although these failures are obviously countercyclical, with the deaths of firms rising when utilization falls in short-term contractions, we think they are also likely to rise over the longer term

15. Growth rates calculated from data in U.S. Bureau of the Census, *Statistical Abstract of the United States, 1981* (GPO, 1981), table 945. The five-year periods reported in the text are constrained by the data reported in the source.

16. See, for example, John W. Kendrick, "Survey of the Factors Contributing to the Decline in U.S. Productivity Growth," in Federal Reserve Bank of Boston, *The Decline of Productivity Growth*, Conference Series 22 (FRBB, 1980), pp. 1–21; and Zvi Griliches, "R&D and the Productivity Slowdown," *American Economic Review*, vol. 70 (May 1980, *Papers and Proceedings*, 1979), pp. 343–48. See also Kim B. Clark and Zvi Griliches, "Productivity Growth and R&D at the Business Level: Results from the PIMS Data Base," Working Paper 916 (National Bureau of Economic Research, June 1982).

17. Based on data on sources and uses of corporate funds in *Economic Report of the President, 1981* (GPO, 1981), table B-87.

when business innovation is most intense. Firms that do not keep pace with or can least afford to keep up with modernization will be more vulnerable to both collapse and bankruptcy when the rate of business innovation is high. Business failures do not *cause* intensification of innovative pressure, according to this argument, but they are *symptomatic* of underlying increases in the forces that spur innovative activity; in other words, the direction of causality is from innovative pressure to business failures and not the reverse.

This supposition is reinforced by the pattern of business failures in the postwar period. Contrary to many expectations, business failures have not risen monotonically with declining utilization rates during the 1970s—although they have obviously soared since 1979 as a result of higher real interest rates. They were much lower in the 1970s, indeed, than during the years of sustained prosperity. We present a decyclical index of the frequency of business failures in figure 2. We have both taken the residuals of a regression of the failure rate on an index of capacity utilization and taken a three-year moving average of that residual to highlight the secular trends. The figure seems consistent with much of the business literature: forces creating business failures rose steadily through the mid-1960s and then declined steadily until the dramatic shift in monetary policy in October 1979 launched interest rates into orbit.¹⁸

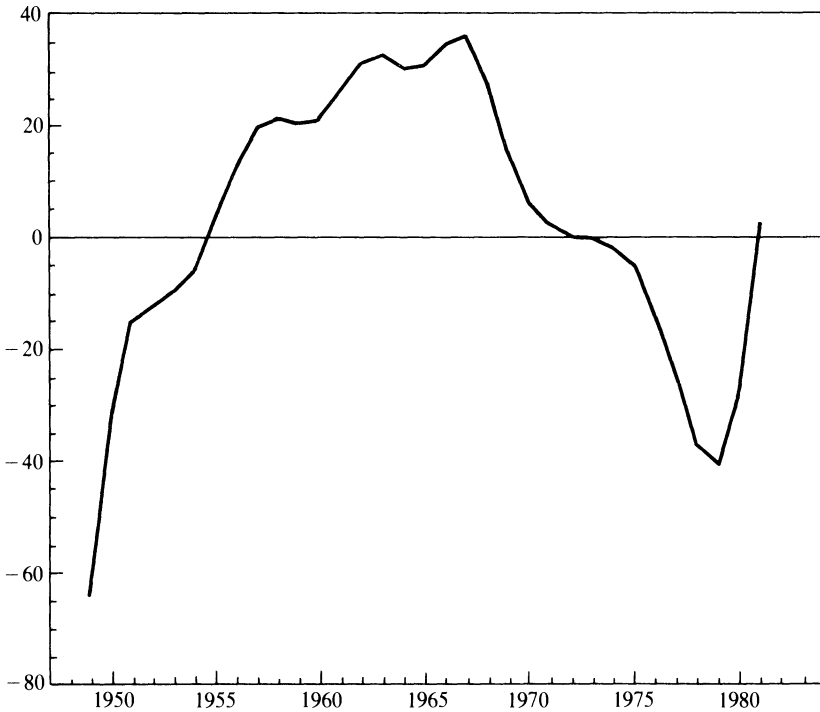
This measure of innovative pressure on business is indirect, as is the evidence on lagging work intensity. It is nonetheless suggestive and more or less consistent with the qualitative and casual observations of the business community. We find it plausible to hypothesize that U.S. corporations have been less likely to pursue productive innovations since the mid-1960s than they had been before. Such a flagging inclination toward productive innovation is likely to have contributed to the productivity slowdown. As the journalist William Greider puckishly observed in a recent article, “When the *Harvard Business Review* discovers that there is something wrong in the executive suite, something is wrong.”¹⁹

18. See the appendix to this paper for definitions and sources. We discuss below some of the problems with using the business-failure rate for these purposes; see the section below, “A Composite Social Model of Aggregate Productivity Growth,” and note 51.

19. William Greider, “Taking Care of Business,” *Rolling Stone*, December 9, 1982, p. 11.

Figure 2. Adjusted Measure of Business Failures, 1949–81^a

*Cyclically adjusted deviations around the mean
(failures per 10,000 enterprises)*



Sources: Authors' estimates based on data from sources cited in the appendix.

a. The original measure of the business failure rate is expressed as the frequency per 10,000 listed enterprises. We then regressed this measure on an index of capacity with annual observations from 1949 to 1979 (the period over which our subsequent econometric work was carried out). We next took a three-year (and end-of-period) moving average of the residuals from the regression, both to control for the short-term business cycle and to smooth the cyclical fluctuations in the underlying measure. The values for 1949, 1950, 1980, and 1981 were based on predicted rather than actual observed residuals from the regression equation.

Determinants of Aggregate Productivity Growth

Conventional analyses of productivity growth have relied on what we call a technical model of production: given existing technical knowledge, labor and nonlabor inputs are routinely and predictably translated into output. The prevailing conclusion derived from this model is that the recent and persistent slowdown in aggregate productivity growth results from the fact, in Martin Neil Baily's words, "either that the rate of technological change is now much slower than it was, or that the effective

flows of capital and labor services have grown more slowly than the measured quantities of these inputs, or perhaps both.”²⁰

We do not doubt that such “technical” factors affect the level of aggregate productivity. But we do question whether such a mechanical model of input-output relations in production could possibly capture the more complex social determinants of aggregate productivity and its growth. We have therefore sought a more complete social model of productivity that treats economic actors as social beings, as people with aspirations and inhibitions, with needs and resentments, with economically important and potentially measurable reactions to their institutional setting and its history. We begin with a separate analysis of the factors affecting work intensity and business innovation and then combine that analysis with hypotheses derived from the more familiar technical model.

WORK INTENSITY: THE MARX EFFECT

Marxian analysis of the labor process has built upon a self-evident proposition: the intensity of human labor in production can vary greatly.²¹

20. Martin Neil Baily, “Productivity and the Services of Capital and Labor,” *BPEA*, 1:1981, pp. 1–2. We have not provided a survey of the mainstream literature on productivity, given its extensive coverage in earlier issues of *BPEA*, but we have found especially useful Edward F. Denison, *Accounting for Slower Economic Growth: The United States in the 1970s* (Brookings Institution, 1979); J. R. Norsworthy, Michael J. Harper, and Kent Kunze, “The Slowdown in Productivity Growth: Analysis of Some Contributing Factors” *BPEA*, 2:1979, pp. 387–421; Kendrick, “Survey of the Factors,” pp. 1–21; and Baily, “Productivity and the Services of Capital and Labor,” pp. 1–50.

21. For some of the most important analytic contributions in the recent literature, see Stephen A. Marglin, “What Do Bosses Do? The Origins and Functions of Hierarchy in Capitalist Production,” *Review of Radical Political Economics*, vol. 6 (Summer 1974), pp. 60–112; Herbert Gintis, “The Nature of Labor Exchange and the Theory of Capitalist Production,” *Review of Radical Political Economics*, vol. 8 (Summer 1976), pp. 36–54; James Devine and Michael Reich, “The Microeconomics of Conflict and Hierarchy in Capitalist Production,” *Review of Radical Political Economics*, vol. 12 (Winter 1981), pp. 27–45; and Samuel Bowles, “The Production Process in a Competitive Economy: Walrasian, Neo-Hobbesian, and Marxian Models” (University of Massachusetts at Amherst, Department of Economics, May 1983).

Some interesting parallels exist between this neo-Marxian literature and some recent neoclassical discussions of hierarchy and involuntary unemployment. See, for example, Guillermo Calvo, “Quasi-Walrasian Theories of Unemployment,” *American Economic Review*, vol. 69 (May 1979, *Papers and Proceedings*, 1978), pp. 102–07; and Edward P. Lazear, “Agency, Earnings Profiles, Productivity, and Hours Restrictions,” *American Economic Review*, vol. 71 (September 1981), pp. 606–20.

We refer to this potential variation in work intensity as the “Marx effect” and rely on some of Marx’s insights into the structure and dynamics of production in capitalist economies in the following analysis of this effect.

Employers will try, other things equal, to minimize the cost in wages, supervision, and other expenditures of a unit of work done. Their tasks are complicated, in large part, because employees will be likely to value positively at least some nonwork activities during work time—which by definition will not contribute to the output of the firm—and will therefore seek to work less intensively than their employers prefer. This presupposition does not imply that work is absolutely unbearable or that all employers apply draconian measures to exploit their workers. It presupposes, much more simply, that employees and employers pursue objectives affecting employee work activity that are not perfectly congruent and are hence potentially in conflict.

We can therefore analyze the employers’ minimization problem by focusing on work intensity, denoted as L^* and defined as the ratio of total effective labor inputs applied in production to the total hours of production-worker labor power hired by the firm. Because effective labor inputs are potentially variable, given purchased labor hours, work intensity is clearly variable as well, suggesting the crucial importance of examining the determinants of its level and variation.²²

A critical determinant of work intensity is the effectiveness of employer control over employees. This depends, in turn, on three main factors: the expected cost of job loss, the probability of being detected if an employee is performing at a level of intensity below management expectations, and the probability of job loss if that poor performance is

22. The analysis in the following discussion draws primarily upon Samuel Bowles, “Competitive Wage Determination and Involuntary Unemployment: A Conflict Model” (University of Massachusetts at Amherst, Department of Economics, 1981); David M. Gordon, “Capital-Labor Conflict and the Productivity Slowdown,” *American Economic Review*, vol. 71 (May 1981, *Papers and Proceedings*, 1980), pp. 30–35; and Juliet B. Schor and Samuel Bowles, “Conflict in the Employment Relation and the Cost of Job Loss,” Working Paper 6 (Economics Institute of the Center for Democratic Alternatives, July 1983). See also Gerry Oster, “Labour Relations and Demand Relations: A Case Study of the ‘Unemployment Effect,’” *Cambridge Journal of Economics*, vol. 4 (December 1980), pp. 337–48; Geoff Hodgson, “Theoretical and Political Implications of Variable Productivity,” *Cambridge Journal of Economics*, vol. 6 (September 1982), pp. 213–26; and Michele I. Naples, “Production Is Human Activity: A Social-Relations Approach to the Productivity Slowdown,” Working Paper 4 (Economics Institute of the Center for Democratic Alternatives, 1982).

detected. The product of these three factors is the expected cost to the employee of working at less intensity than is expected by management.²³

The first of the three is the most obvious. Since employers in capitalist economies may not physically coerce their workers or deprive them of their liberty, one powerful instrument of employer influence is dismissal—the threat of which will depend on the cost to workers of losing their jobs. The higher the cost of job loss, the more fearful workers will be of failure to conform to employers' intentions.

The probability of detection depends on the intensity of supervision—that is, surveillance and direction of production workers on the job. The probability of dismissal varies inversely with the extent of formal power of the employee based on unions and other collective employee associations and the difficulty the employer will have in replacing the worker.²⁴

The multiplicative relation among these three factors implies complementarity, as seems reasonable: intense supervision will do little good if there is no cost to loss of job or if the probability of dismissal is low, for example, and costly job-loss conditions will have little effect if employers are incapable of detecting and dismissing those deserving punishment.

These hypotheses suggest the following expression for the factors affecting work intensity:

$$(1) \quad E = J \cdot S \cdot D(U, R),$$

$$E_J, E_S, E_D, E_{JS}, E_{JD}, E_{SD} > 0, \quad D_U < 0, D_R > 0,$$

where

E = index of the effectiveness of employer control over workers

J = expected income loss resulting from job loss

S = ratio of supervisory-worker hours to production-worker hours

D = index of the probability of dismissal if detected working below management expectations

23. See Bowles, "The Production Process in a Competitive Economy," for a formal argument about the multiplicative nature of this relationship.

Our formulation here attempts to model "objective" or "material" factors affecting work intensity, and therefore avoids treating worker attitudes as purely "exogenous." We think that this approach is preferable to that of analysts such as Norsworth and Zabala, in "Worker Attitudes and the Cost of Production," who implicitly treat "worker attitudes" as a fully exogenous factor and do not seek to understand what determines variations in that determinant of costs and productivity.

24. The logic underlying the second of these conditions is similar to that of the search-theoretic analysis of the conditions affecting employers' decision to hire a new employee or to continue searching.

U = level of collective worker membership in unions or other employee associations

R = index of conditions affecting the ease with which management believes it can replace a dismissed worker.

Worker motivation is likely to constitute the second major determinant of work intensity. If there are substantial improvements in workers' earnings or working conditions that result from increases in their intensity of work, for example, workers may be more inclined to cooperate with efforts to boost productivity. Conversely, if they must accept lower wages to foster investment or suffer speedup and hazardous working conditions to permit productivity increases, they may be more likely to intensify their resistance to employers' efforts to extract more labor activity.

It seems likely, then, that

$$(2) \quad M = M(W!, B, M^*), \quad M_{W!}, M_B, M_{M^*} > 0,$$

where

M = index of workers' motivation

$W!$ = motivation-enhancing factors in workers' earnings

B = index of quality of working conditions

M^* = vector of any exogenous factors that positively influence workers' job satisfaction.

We can combine equations 1 and 2 to form a composite expression for the determination of work intensity. Despite the obvious limitation that variations in the level of work intensity cannot be measured directly, it then becomes possible to specify the form of the functional expressions implied by 1 and 2 and, as shown below, to measure—albeit imperfectly—their several components. This further step makes it possible to draw inferences about unmeasurable variations in work intensity from variations in factors that are likely to cause work intensity to vary; thus we can incorporate analyses of the factors determining the intensity of work into a more general model of the determinants of productivity.

INNOVATIVE PRESSURE ON BUSINESS: THE SCHUMPETER EFFECT

Mainstream analyses of the aggregate production function implicitly assume a standard neoclassical model of competition: with conditions

of perfect competition presumed, the forces of competition remain constant and continuous for the individual firm. As the production-possibility frontier moves outward, firms are forced to remain on the frontier because of the unrelenting force of continuing competitive pressure. We call this the assumption of automatic technical adaptation.

Marx and Schumpeter suggested a quite different conception of competition. Marx originally argued that competition, while unrelenting, was more like warfare than a harmony of mutual exchanges; far from acting as passive price-takers, firms engage continuously in attack and counterattack, in foray and retreat.²⁵ Schumpeter substantially extended these insights. He suggested that innovative breakthroughs create transitory monopoly power and generate quasi rents to be collected by the innovator, so that subsequently competitors are compelled to imitate those innovations. In later work on business cycles and long waves, Schumpeter argued that there are periodic waves of corporate innovation and entrepreneurial energy. These waves of innovation also unleash, according to Schumpeter, "gales of creative destruction." The firms least able to ride the waves of innovation fall behind or fail.²⁶

These insights suggest that variations in innovative pressures on business substantially affect the level and growth of aggregate productivity. Automatic technical adaptation to exogenously generated technical progress implies, other things being equal, a relatively steady rate of adaptation to exogenously generated expansion of productivity-enhancing knowledge. If, however, there are variations in the pressure on firms to adopt new methods for improving productive efficiency, exogenously generated technical knowledge, even if growing at a constant rate, will not lead to a steady rate of increase in aggregate productivity. When competitive pressures are high, other things being equal, productivity growth will also increase. When competitive pressures slacken, productivity growth is also likely to moderate.²⁷

25. For useful discussions of Marx's conception of competition see Anwar Shaikh, "Political Economy and Capitalism: Notes on Dobb's Theory of Crisis," *Cambridge Journal of Economics*, vol. 2 (June 1978), pp. 233–51; and Willi Semmler, *Competition and Monopoly* (Columbia University Press, forthcoming).

26. See Joseph A. Schumpeter, *The Theory of Economic Development* (Harvard University Press, 1934); *Business Cycles*, vol. 1 (McGraw-Hill, 1939); and "The Analysis of Economic Change," *Review of Economics and Statistics*, vol. 17 (May 1935), pp. 2–10.

27. We should note as an addendum that our analysis of innovative pressures (and of business failures) may be distinguished from two strands of prevailing discussion in the

This hypothesis can be translated into a form that permits direct incorporation into a model of aggregate productivity growth. Many neoclassical growth models suggest that technical advance contributes to aggregate productivity growth exponentially over time, reflected in the exponential adjustment factor, $e^{\lambda t}$. Relying on what we call the Schumpeter effect, we substitute a behavioral relation for the constant parameter λ .

We begin with the proposition that the actual rate of implemented technical progress is a function of both the exogenous growth of potential technical progress and the current levels of innovative pressure on business:

$$(3) \quad \lambda = \lambda^* + \mu C, \quad \mu > 0,$$

where

λ = actual rate of technical progress

λ^* = rate of growth of exogenously generated technical knowledge

μ = coefficient of a firm's adjustment to variations in competitive pressure

C = index of the (variable) level of competitive pressure on firms to improve productive efficiency, with a mean of $\bar{C}$ equal to zero.

This formulation suggests that the neoclassical model is simply a special case: if competitive pressure were constant (and equal to $\bar{C}$), the

business and economics literature. One emphasizes changes in business attitudes or risk preferences as a source of variations in innovative pressure. This is especially characteristic of recent journalistic discussions of management failures in the United States. A second, following the Schumpeterian lead, places emphasis on purely technical determinants of waves of innovative pressure, focusing on bursts of invention and subsequent diffusion of "epoch-making" ideas. For a justifiably critical review of this approach, see Edwin Mansfield, "Long Waves and Technological Innovation," *American Economic Review*, vol. 73 (May 1983, *Papers and Proceedings*, 1982), pp. 141–45. We argue in contrast that long swings in innovative pressure reflect and are conditioned by the construction of new social structures of accumulation and the long periods of expansion they support. We concentrate, in other words, on structural forces affecting innovative pressures rather than on changes in attitudes or trends in technical inventiveness. For further elaboration, see David M. Gordon, Richard Edwards, and Michael Reich, *Segmented Work, Divided Workers: The Historical Transformation of Labor in the United States* (Cambridge University Press, 1982), chap. 2; and David M. Gordon, Thomas E. Weisskopf, and Samuel Bowles, "Long Swings and the Nonreproductive Cycle," *American Economic Review*, vol. 73 (May 1983, *Papers and Proceedings*, 1982), pp. 152–57.

actual rate of growth of technical knowledge would be equal to λ^* . But if competitive pressure were not constant, then C would vary, and λ would thus diverge from λ^* .

These propositions further suggest that variations in innovative pressure have a cumulative effect, augmenting or eroding a firm's inclinations to innovate over a period of years defined primarily by the firm's planning horizons and the average amortization period of technical innovations. Short-term cyclical variations in innovative pressure are less likely to affect a firm's behavior than sustained trends toward more or less intense competition over substantially longer periods. Assuming that we can find a reasonable proxy measure for C and that we can properly cumulate its effects over time, the Schumpeter effect should be just as susceptible to analytic investigation as the Marx effect.

TECHNICAL FACTORS AFFECTING PRODUCTIVITY

Our attention to the Marx and Schumpeter effects is in no way intended to diminish the importance of relations highlighted by the more familiar technical model of productivity. We expect that the level of capacity utilization, the capital intensity of production, and variations in the relative prices of external inputs all affect aggregate productivity. We note here the main directions of effect.

Capacity Utilization. There are several important reasons for expecting covariation between aggregate labor productivity and capacity utilization. First, there might be hoarding of nonproduction workers in business-cycle downturns, which would lead to reduced labor productivity (per purchased total labor hours) during recession. Second, and similarly, there would be underutilization of owned fixed-capital stock during a downturn, which would lead to decreased actual use of capital inputs in production. Third, the efficiency of the production process itself—including the efficiency of utilized capital inputs and of the labor-management apparatus—might be reduced if capacity utilization fell below some targeted or warranted level for which productive operations had been designed. Fourth, it is conceivable that there might be some hoarding of production workers during the cycle, with explicit or implicit contracts preventing the immediate layoffs that lower capacity utilization might otherwise cause. A fifth factor might have the opposite effect: during periods of low capacity utilization, firms might retire their least

efficient capital equipment and thus increase the average productiveness of capital goods still in use.

In the subsequent analysis we control for the first two factors directly. Hoarding of nonproduction workers during the business cycle is taken into account by expressing productivity as output per production-worker hour. Variable utilization of the fixed capital stock over the cycle is tested by adjusting measures of the owned fixed-capital stock for variable levels of utilization.

The net effect of the last three factors is impossible to anticipate *a priori*. We weigh the relative importance of offsetting possible effects of lower capacity utilization by testing directly for the direction of covariation, other things equal, between aggregate productivity and the level of capacity utilization. We control for the possibility of sluggish adjustment of staffing levels to the business cycle by postulating that aggregate productivity will also vary directly with the rate of change of capacity utilization; the more rapidly utilization levels are increasing, for example, the greater is the likelihood that firms will make increasingly efficient use of the resources and the employees that might have been partly idle during periods of contraction. These controls are obviously rough and imperfect, but they should at least allow testing of hypotheses about other possible determinants of aggregate productivity by provisionally controlling for the possible influence of variations in capacity utilization.

Capital Intensity. Aggregate labor productivity clearly varies with the capital intensity of production. But aggregate capital intensity cannot be measured by the aggregate ratio of the (value of the) owned capital stock to labor hours for at least two important reasons. First, some portion of the owned capital stock may not enter into production; it lies unutilized as a result of fluctuations in aggregate effective demand. Second, there may be significant variations in the average efficiency of effective capital services, resulting primarily from the possibility of obsolescence in the capital stock not captured by the usual adjustments for depreciation.

These considerations clearly suggest the need for two independent kinds of adjustments to the aggregate capital-labor ratio—one for variable levels of utilization and another for factors that may lead to variable rates of obsolescence. We pursue both kinds of adjustments in succeeding sections of the paper, although the former is much easier to specify than the latter.

External Input Prices. Several economists, particularly Michael Bruno and Jeffrey Sachs, have recently focused on the effects of input price shocks on productivity growth in the United States and other advanced economies. Bruno states their conclusion quite simply:

For a raw-material intensive activity the conventional two-factor view of the production process is only valid when the relative price of the raw material (in output units) or its unit input stays constant. When its relative price rises and it is a complementary factor of production, productivity per unit of the other factors, labour and capital, must fall.²⁸

We agree with the microeconomic presuppositions of this argument; increases in external input-prices of crude and intermediate materials are likely to reduce the productivity of labor and capital inputs. We are concerned, however, about the way in which this insight is applied and about the specification of relative input prices in the recent literature. We make an effort in subsequent sections to improve upon the empirical specification of this effect.²⁹

A Composite Social Model of Aggregate Productivity

It is now possible to combine both social and technical dimensions into a composite model of aggregate labor productivity. We follow convention and express productivity as a multiplicative function of the several inputs and social factors that are likely to affect it.³⁰ The basic model becomes

28. Michael Bruno, "World Shocks, Macroeconomic Response, and the Productivity Puzzle," Working Paper 942R (National Bureau of Economic Research, July 1982), p. 2. See also Michael Bruno, "Raw Materials, Profits, and the Productivity Slowdown," Working Paper 660 (National Bureau of Economic Research, April 1981); and Bruno and Jeffrey Sachs, "Input Price Shocks and the Slowdown in Economic Growth: The Case of U.K. Manufacturing," Working Paper 851 (National Bureau of Economic Research, February 1982).

29. We note for purposes of clarity that Bruno actually identifies two alternative possible effects of relative external price increases on productivity growth. One is the substitution effect, illustrated by the quotation in the text. The other focuses on the measurement bias resulting from the standard procedure of double deflation of gross output data in the national accounts. As Bruno notes, it is difficult to separate the two.

30. The crucial assumption in this formulation that cannot be avoided is that of constant returns to scale, and we comment on the relevance of and evidence for this assumption as the econometric tests proceed. See note 54 below. For a detailed critique of the traditional inferences about aggregate production functions, see Anwar Shaikh, "Laws of Production and Laws of Algebra: The Humbug Production Function," *Review of Economics and Statistics*, vol. 56 (February 1974), pp. 115–20.

$$(4) \quad Q = AG^{\alpha_1} (1 + G')^{\alpha_2} K^{*\beta} L^{*\gamma} P_x^\delta e^{(\lambda^* + \mu C)t},$$

with

$$\alpha_1, \alpha_2, \beta, \gamma, \lambda^*, \mu > 0, \quad \delta < 0,$$

where

Q = total output per unit of purchased production labor inputs

A = positive constant

G = level of aggregate capacity utilization

G' = index of rate of change of that utilization

K^* = utilized, nonobsolescent capital inputs per hour of purchased production labor inputs

L^* = amount of effective labor inputs per hour of purchased labor inputs

P_x = index of the relative price of external inputs

C = index of the level of innovative pressure on firms to improve productive efficiency.

Comparative hypotheses about the sources of the productivity slowdown require that we move from this expression for determinants of the level of aggregate labor productivity to a focus on changes in productivity over time. We denote x as the logarithmic rate of change of X per unit of time, substitute from expressions 1 and 2 into 4, and introduce γ_1 and γ_2 as coefficients of adjustment mediating the two determinants of work intensity. The following general expression for changes in aggregate labor productivity over time is thus obtained:

$$(5) \quad q = \lambda^* + \alpha_1 g + \alpha_2 \Delta g + \beta k^* + \gamma_1 e[J \cdot S \cdot D(U, R)] \\ + \gamma_2 m(W!, B, M^*) + \delta p_x + \mu C,$$

with

$$\lambda^*, \alpha_1, \alpha_2, \beta, \gamma_1, \gamma_2, \mu > 0, \quad \delta < 0.$$

We next provide a specification and econometric estimation of our general social model of productivity growth, as summarized by equation 5. We also compare its explanatory power with that of models derived from the more conventional technical explanations of the productivity slowdown.

MODEL SPECIFICATION

We estimate the model with annual data for the postwar years from 1948 to 1979 because these end points were business cycle peaks and we

sought to estimate over the full range of completed business cycles during the postwar period for which all necessary data were available. (Complete annual—but not quarterly—data series are available for our desired variables only between 1948 and 1979.) We focus on the nonfarm private business sector in the United States, excluding both the farm and government sectors on the grounds that their dynamics and production processes are not adequately captured by the model developed in the previous section. We review our specification of each of the variables in our general social model in the order in which they appear in equation 5. (See the appendix for full documentation of the data sources.) When we introduce variables, we normally define them first in terms of their levels, referring back to the original expression for the level of aggregate productivity in equation 4, and then transform them into rates of change for estimation of equation 5.

Hourly Output. We specify the dependent variable as the rate of change of real output per hour of production-worker employment. To obtain this measure of hourly output, we use basic indexes of nonfarm business output and total hours by the Bureau of Labor Statistics, and adjust total hours in the denominator by the ratio of production-worker employment to total employment.³¹

We define the productivity measure in relation to production-worker hours, rather than total worker hours, in order to focus on the differing activities of directly productive labor, on the one hand, and surveillance or supervisory labor, on the other. (We use standard BLS data to define production workers as “production” employees in the goods-producing sectors and as “nonsupervisory” employees in the rest of the nonfarm private business sector. Workers in this combined category comprised

31. Some economists are skeptical of “value-added” measures of productivity and prefer to limit themselves to “physical” measures of output in the numerator. The latter are available in the United States only through the Federal Reserve Board series on manufacturing output. Although we recognize that value measures introduce some potential “noise” into the measure of total output, we feel comfortable with the value-added measures for the purposes of this paper for two reasons. First, there are some obvious advantages to being able to develop analyses for the entire nonfarm private business sector, but physical measures of output are available only for manufacturing. Second, and much more important, it does not appear that the physical and value-added series tell a substantially different story for the manufacturing sector for the postwar economy. For one useful comparison of the two series for manufacturing, see Tom Michl, “The Lowdown on the Slowdown” (New School for Social Research, Department of Economics, 1982).

81.3 percent of total private employment in 1980.) This choice of a denominator for the output variable recognizes that the specific nature of the contribution of supervisory labor to production is qualitatively different from that of production workers; its contribution lies substantially in extracting work from directly productive workers rather than directly transforming raw materials and intermediate goods into final outputs. We show below that our empirical results are robust with respect to this and alternative specifications of the dependent variable.

Capacity Utilization. The Bureau of Economic Analysis data on the ratio of actual to potential GNP, as adjusted periodically by the Council of Economic Advisers, are used to measure economy-wide capacity utilization. This ratio tracks the year-to-year movements of the business cycle and is used to measure the impact of those fluctuations on aggregate labor productivity.³²

Capital Intensity. The fixed-capital stock in the nonfarm business sector is taken from the recently published Bureau of Economic Analysis data. Conforming to our definition of hourly output and of productive-labor inputs, we divide the capital stock by estimated production-worker hours to derive an estimate of the capital-labor ratio. Because only utilized capital inputs augment hourly productivity, we adjust the capital stock by the rate of capacity utilization (as defined above), with K_u as the utilized capital-labor ratio. This procedure means that the rate of change of capacity utilization enters the model twice—once directly and once as a component of the measure of the rate of change in the utilized capital-labor ratio; it also means we have to interpret the coefficients on both variables carefully. This formulation is nonetheless preferred for the purposes of initial estimation because it more directly assesses the contribution of fluctuations in the capital services actually applied in the production process than a measure of the unadjusted capital-labor ratio or a measure of the ratio of the owned capital stock to potential GNP.³³ Again, we examine the sensitivity of the results to this particular formulation in subsequent estimations.

32. We also considered and explored two alternative measures of capacity utilization and cyclical variation—the Federal Reserve Board's series on capacity utilization and the aggregate unemployment rate. The disadvantage of the former is that it is only available for manufacturing, and not for the total nonfarm private business sector; the disadvantage of the latter is that it reflects effects of both labor supply and demand.

33. We share some of the skepticism of Cambridge, England, about the plausibility of aggregate measures of the value of heterogeneous capital goods, but we suspect that these

The issue of the relative obsolescence of capital is more complicated, and there are no clear guidelines in the available literature.³⁴ Following the interesting suggestions of Martin Neil Baily, we have formulated several provisional specifications of the hypothesis that the contribution of capital services depends on variations in the degree of obsolescence of the capital stock, but we discuss these additional tests in the succeeding section because of their speculative (and largely inconclusive) nature.

Work Intensity. We specify the Marx effect through direct estimation of all components of L^* included in equation 5 for which it was possible to obtain annual empirical data.

The effectiveness of employer control is a function of three variables, J , S , and D . Relying on separate work by Juliet B. Schor and Samuel Bowles, we measure J , the cost of job loss, by a composite measure of the expected income loss resulting from job termination:³⁵

$$(6) \quad J = U_d [(W - W_R)/(W + W_s)],$$

where

U_d = average unemployment duration for job losers, expressed as a fraction of a year

W = average production-worker weekly after-tax earnings

criticisms are more relevant for the debates about the marginal productivity of capital than for the econometric investigation of alternative hypotheses concerning the productivity slowdown. As long as the biases in aggregate value measures of the capital stock are relatively consistent over time, for example, then changes in the rate of growth of the measured capital stock, and therefore in our measure of capital intensity, are likely to provide plausible indications of changes in the physical ratios of capital goods to labor hours and, consequently, of changes in the contribution of capital goods to the productivity of labor hours over time.

We also considered formulating our variable for capital intensity as the ratio of the owned capital stock to potential output, with an eye on trends in potential (but not actually utilized) capital intensity. This seems to us a theoretically inferior specification since it is distorted by lags in the adjustment of investment (and therefore changes in the value of the capital stock) to changes in the trend growth of both output and productivity; it does not directly measure the value of the capital stock, which enhances labor productivity, but focuses instead on the capital that might augment it. We tested this specification in our estimation of equation 8, in any case, and the capital intensity variable became statistically insignificant.

34. See the discussion in Baily, "Productivity and the Services of Capital and Labor"; and Barry P. Bosworth, "Capital Formation and Economic Policy," *BPEA*, 2:1982, pp. 286-90.

35. See Juliet B. Schor and Samuel Bowles, "Conflict in the Employment Relation and Cost of Job Loss."

W_R = average weekly income-replacing benefits received by those without work, including a weighted allocation of unemployment compensation, public assistance, food stamps, and medical care benefits, to reflect relative worker eligibility for those different streams of benefits

W_s = average weekly nonincome-replacing benefits, particularly including education and medical benefits.

Defined in this way, J measures the fraction of a year's overall income (including both wages and government expenditures) that a worker can expect to forgo as a result of job loss.

The intensity of supervision, S , is measured as the ratio of nonproduction-worker hours to production-worker hours in the nonfarm private business sector.³⁶

We measure D , the probability of dismissal should a worker be detected performing at a level of intensity below management expectations, by specifying the two components identified in equation 1. We define U as the percentage of the nonagricultural labor force that is unionized. We define R as the ratio of trend production-worker employment to its current levels; the greater is the ratio of trend to actual levels, the more slack there is in the current production-worker labor force and therefore the easier it is to replace a production worker who is not cooperative on the job.

36. Many who have heard us present our work have questioned the relevance of this measure of the intensity of supervision on the grounds that it includes too many technical workers to warrant its use as a proxy for supervisory labor. We rely on the data distinction in standard Bureau of Labor Statistics compilations between production and nonproduction employees in the goods sectors and nonsupervisory and supervisory employees in the service sectors. It is true that some of the employees designated by official data as nonproduction or supervisory personnel are not managers, clerical supervisors, or foremen, but by far the largest proportion do indeed fall into those three categories.

In 1980, for example, there were 13.9 million nonproduction and supervisory workers on private nonfarm payrolls as defined by the BLS definitions we apply in our statistical work. In that same year, according to the more detailed three-digit occupational categories of the U.S. Bureau of the Census, there were approximately 11.5 million managers, clerical supervisors, and blue-collar supervisors in the private sector. (This approximation assumes that the same proportions of workers worked in those categories in both the public and private sectors.) Even in 1980, therefore, at the end of a long period of rapid growth in technical employment it remained true that at least 83 percent of workers in this data category were explicitly classified as managers and supervisors.

In the absence of compelling theoretical guidelines, a multiplicative form for D is arbitrarily adopted:

$$(7) \quad D = \sqrt{R \cdot U^{-1}} = \sqrt{(\hat{L}p/Lp_t)/U},$$

where U is defined as above and $\hat{L}p$ measures the time trend of production-worker hours, Lp_t , for 1948–79.³⁷

In this paper we focus on two of the three variables contained in the functional expression for changes in workers' motivation, m , in equation 5. We measure w by the rate of change in workers' real spendable hourly earnings, hypothesizing that workers' motivation is higher, as is their work intensity, the more rapidly their take-home pay increases.³⁸ We express an imperfect proxy for B , the index of the quality of working conditions, as the inverse of Z , the industrial accident rate; thus $B = Z^{-1}$. We postulate an inverse relation between the accident rate and workers' motivation. According to this formulation, rising accident rates are likely to erode the quality of working conditions, reduce workers' motivation, and therefore diminish work intensity.³⁹

We had hoped to find an annual measure of workers' job satisfaction to serve as a proxy for M^* , which also affects worker motivation. We could not find a suitable annual series for the entire period of observation and thus were unable to include a measure of M^* in our equation.⁴⁰

37. We plan to explore the effects of a variety of possible specifications in the future; for the moment, since the variable J carries the greatest statistical weight in the econometric applications reported below, we retain this simple multiplicative definition and save for other efforts a more careful analysis of the most appropriate form of interaction among the two constituent variables of D . We take the square root of the expression in equation 7 to avoid artificial amplification of the variance of the composite variable.

38. This hypothesis seems particularly relevant for unionized production workers in the United States in the postwar period because it corresponds to the logic of collective bargaining over the distribution of the dividends from productivity growth—to what has usually been called, indeed, productivity bargaining.

39. One could alternatively hypothesize that the accident rate primarily reflects speedup on the job and that a rising accident rate would therefore be accompanied by an increase in work intensity, not a decrease. The actual estimated results for the effects of Z should help to discriminate between these two possibilities: a negative and statistically significant effect of Z on hourly output would suggest that the negative impact of a speedup on worker motivation swamps any direct positive effect on work intensity, while a positive effect on productivity would indicate the opposite.

40. We note with interest, however, that the series on job satisfaction available on a consistent though intermittent basis since the mid-1950s reports trends that are parallel to trends in productivity growth and support our hypotheses about spreading disaffection since the 1960s. See the first major section of this paper and note 7 above.

External Input Costs. We begin by measuring the relative price of external input costs by P_f , an index of the relative price of fuels. This choice reflects the importance placed on oil prices in the mainstream literature.⁴¹ We are not content with this measure, however.

A variety of external inputs exists whose supply can be subject to shocks and whose relative price might therefore increase and adversely affect the productivity of other factors of production. For the domestic private nonfarm business sector in the postwar period, such shocks have occurred in the production and pricing of many nonagricultural raw materials, not just oil and coal. This has been due to both foreign and domestic effects. Internationally, OPEC and other suppliers have combined to produce sharp increases in the price of imported oil and a few other imported crude materials. Domestically, popular resistance to the physical and environmental effects of energy production—embodied in the movement for environmental regulation, the campaign against nuclear power, and the mine workers' struggles for greater safety in the mines—have combined to increase the relative production costs of domestic nonagricultural crude materials. These two developments have jointly affected the relative costs of external inputs consumed by the domestic private nonfarm business economy.⁴²

We capture this effect with an alternative variable representing external input prices, P_x , measured as the relative cost of nonagricultural crude materials, which we calculate by dividing an index of the prices of fuels and other crude materials (excluding foodstuffs and feedstuffs) by the aggregate GDP price deflator.

The performance of these two alternative measures of relative external input prices is compared throughout the rest of the analysis. Even at this

41. For a summary of much of this literature see Ernst R. Berndt, "Energy Price Increases and the Productivity Slowdown in United States Manufacturing," in Federal Reserve Bank of Boston, *The Decline in Productivity Growth*, pp. 60–89. Technically it ought to be possible to capture the substitution effect of relative external input price shocks by measuring changes in the relative quantities of energy inputs, rather than in their prices, and to rely on price measures to test for the effect of measurement bias resulting from double deflation of gross output measures (see note 29 above). In practice, however, quantity measures do not provide additional explanatory power in the econometric results reported below, so that we are constrained for empirical reasons to rely exclusively on relative price measures of this effect. See the text below for a discussion of the effect of a quantity measure of energy inputs.

42. See the discussion in Bowles, Gordon, and Weisskopf, *Beyond the Waste Land*, pp. 91–94 and 136–38.

stage of initial specification, the principal differences are evident. The index of relative fuel prices pays attention to only one category of external inputs and therefore tends to confuse a particular instance of recent price shock with the more general political economic problems of sluggish supply responses, occupational safety, and environmental problems. The fuels covered in the index of relative fuel prices, indeed, account for only about one-third (by value weights) of the total value of inputs included in the nonagricultural crude-material price index. This index, because of its focus on the price of imported oil, also tends to give too much attention to a single type of foreign shock—the successive OPEC price hikes—and too little to other domestic movements that also affect relative input prices of crude materials.⁴³

Innovative Pressure on Business. Following Schumpeter's clues about creative destruction, we focus on the rate of business failures as an indirect measure of the pressure on business firms to remain competitive and adopt available technical innovations. Data for the business-failure rate are available on a continuous basis throughout the postwar period. Use of this variable does not imply that business failures are the only or most important cause of productive innovation but that variations in the business-failure rate reflect and themselves directly covary with a wide variety of factors affecting business innovation for which continuous annual data are not available throughout the postwar period.

Further applying the supposition that variations in innovative pressure have cumulative effects, we transform the business-failure rate to eliminate short-term cyclical variation and to highlight its more secular trends. We residualize the business failure rate on the level of capacity utilization and then take a three-year (end-of-period) moving average of this residualized variable. We label this variable C^* . This involves the hypothesis that recent variations in the business-failure rate that are not simply functions of fluctuations in the level of capacity utilization can provide a proxy measure of recent trends in the intensity of innovative pressure on firms.⁴⁴ We further test the robustness of this specification

43. We place heavy emphasis in our book on the role of domestic and international "popular resistance" as a source of rising external input prices after the mid-1960s. This involves an argument about and an interpretation of our variable for external input prices that cannot be further explored through the econometrics of this paper; see *ibid.*, chaps. 4 and 6.

44. In background work for this paper we developed a model of the failure rate that supports this interpretation. We show that, when one controls for the level of capacity

by exploring several alternative variables based on the business-failure rate.

EMPIRICAL ESTIMATION

Based on these variable definitions, we arrive at a final specification of equation 5 for the purposes of initial econometric estimation:

$$(8) \quad q = \lambda^* + \alpha_1 g + \alpha_2 \Delta g + \beta k_u + \gamma_1 e \\ + \gamma_{21} \Delta w! + \gamma_{22} z + \delta p_x + \mu C^*,$$

where the variables are defined as above. We hypothesize that the coefficients λ^* , α_1 , α_2 , β , γ_1 , γ_{21} , and μ are positive and that γ_{22} and δ are negative. As in standard econometric estimation, we assume a stochastic component in the dependent variable, with u_t distributed with zero mean and σ^2 variance.⁴⁵

Two considerations influenced the empirical work: first, since we could not assume a priori that our hypotheses about the effects of our unfamiliar and unconventional “social” variables were associated with changes in aggregate productivity, it seemed crucial to test these hypotheses against the null hypothesis of no significant statistical association.⁴⁶ Furthermore, although we preferred to estimate equation 8 directly, rather than use a modified version of the aggregate production function with output as the dependent variable and a measure of labor

utilization and the cost of capital, variations in the failure rate are almost completely explained by trends in capital intensity, and a trend term that closely mirrors the pattern reflected in figure 2—suggesting a smooth and inverted U-shape trajectory in the determinants of the failure rate in the postwar period.

We chose a three-year period for the moving average of the failure rate because this is the length of the period over which past values of the rate are significant in explaining its current values in an autoregressive estimation.

45. We use ordinary least squares estimation in the tests reported here, a simple choice that does not appear to require emendation as a result of the specification or the results themselves. See the text below for comments on potential simultaneous equation bias and autocorrelation.

We add here the more inclusive measure of external input prices, p_x , because we believe it better captures the political economic determinants of variations in external input prices. Below we compare its performance with the narrower measure, p_f .

46. One of the most glaring presumptions of the accounting-method approach is its axiomatic application of the marginal-productivity theory of wages to the adjustments for “quality” in estimating labor. See the critical discussion of this procedure in the section entitled “Extensions and Competing Hypotheses” below.

hours on the right-hand side of the equation, we test the sensitivity of our results to this particular specification.⁴⁷

We show below the average values for the dependent variable, the average annual growth in real output per production-worker hour, for the entire period, 1948–79, and for three subperiods in which, as the previous literature attests, the productivity slowdown is most clearly revealed.⁴⁸ These data are consistent with other estimates in the literature. Differences in estimates of the timing and magnitude of the productivity slowdown primarily are in the levels of subperiod growth rates. If we compare our estimates with those of Martin Neil Bailly, for example, the productivity growth rates estimated here are higher for every subperiod, but the relative magnitudes of decline from one period to the next are roughly comparable; the higher growth rates estimated here are due to the use of production-worker hours as the denominator in the measure of hourly output, since total worker hours grew at a more rapid rate than production-worker hours during the postwar period.⁴⁹

	<i>Average annual rate of growth (percent)</i>
1948–79	2.34
1948–66	2.87
1966–73	2.19
1973–79	0.85

47. Our preferred specification focuses directly on the object of analysis—variation in the rate of change of productivity—and poses a more stringent test for the explanatory power of the various independent variables in the analysis.

One danger of this specification, of course, is that we may compound the problem of potential errors in variables by including labor hours in the denominator on both the left- and right-hand sides of the equation. We test for this possible bias below by comparing our basic results with a specification in which only output appears on the left-hand side of the equation and labor hours appears as an independent variable.

48. Productivity growth is defined as the average annual logarithmic rate of growth of output per production-worker hour. The averages are calculated as the means of the individual annual growth rates, since these are the actual observations for the dependent variable in subsequent econometric estimation. See Bowles, Gordon, and Weisskopf, *Beyond the Waste Land*, chap. 2, for further justification of these periods for comparison.

49. See Bailly, “Productivity and the Services of Capital and Labor,” p. 9. Growth rates for the counterpart to our dependent variable defined as output per total-worker hour for the entire period and the three subperiods reported in table 1 were 2.08, 2.56, 2.10, and 0.63 percent, respectively.

Table 1. A Social Model of Aggregate Productivity Growth in U.S. Nonfarm Private Business, 1948–79^a

Independent variable	Equation						
	1-1	1-2	1-3	1-4	1-5	1-6	1-7
Trend growth rate, λ^*	0.015 (7.98)	0.016 (6.35)	0.016 (7.97)	0.004 (1.02)	0.015 (6.92)	0.017 (8.07)	0.017 (8.39)
Capacity utilization							
g	0.485 (4.80)	0.519 (4.43)	0.449 (4.68)	0.419 (4.58)	0.408 (3.47)	0.442 (4.48)	0.415 (4.41)
Δg	0.074 (1.33)	0.049 (0.78)	0.082 (1.48)	0.094 (1.74)	0.091 (1.50)	0.125 (2.29)	0.103 (1.96)
Utilized capital-labor ratio, k_u	0.401 (4.64)	0.385 (4.26)	0.411 (4.74)	0.419 (4.99)	0.472 (5.29)	0.373 (4.17)	0.373 (4.26)
Effectiveness of employers' control, e	0.035 (3.74)	...	...	...	...	...	...
Real spendable earnings, $\Delta w!$	0.075 (1.68)	0.073 (1.57)	0.072 (1.60)	0.069 (1.57)	0.121 (2.71)	0.292 ^b (1.37)	...
Accident rate, z	-0.083 (-3.50)	-0.088 (-3.38)	-0.086 (-3.60)	-0.087 (-3.74)	-0.100 (-3.29)	-0.081 (-3.23)	...
Relative external input prices, p_x	-0.040 (-2.13)	-0.042 (-2.13)	-0.041 (-2.14)	-0.037 (-1.95)	-0.013 ^b (-0.52)	-0.048 (-2.62)	-0.055 (-3.27)
Business failure measure, C^*	0.011 (2.81)	0.011 (2.72)	0.011 (2.75)	0.020 ^b (2.98)	0.012 (2.43)	0.010 (2.50)	0.008 (2.20)
Cost of job loss, j	... (3.72)	0.036 (3.72)	0.034 (3.60)	0.031 (3.41)	0.027 (2.74)	0.027 (2.48)	0.034 (3.58)
Supervision intensity, s	...	0.001 (0.01)	...	...	...	...	...
Probability of dismissal, d	...	0.100 (1.20)	...	...	...	...	...
Predicted job satisfaction, $m!$	...	...	...	...	...	...	0.450 (3.74)
Summary statistic							
$\bar{R}^2$	0.913	0.908	0.910	0.914	0.893	0.906	0.909
Standard error of estimate	0.005	0.005	0.005	0.005	0.005	0.005	0.005
Durbin-Watson	2.095	1.891	2.092	2.200	2.184	2.214	2.096

Source: Authors' estimates based on data cited in the appendix.

a. The dependent variable is the rate of change in output per production-worker hours, measured as change in logs. The independent variables are all growth rates measured as change in logs, with the exception of C^* , which is a level variable, and Δg and $\Delta w!$, which are first differences of changes in logs. Given first differences, the actual observations are for 1949–79. The numbers in parentheses are t -statistics.

b. The values for C^* (equation 1-4), p_x (equation 1-5), and $\Delta w!$ (equation 1-6) are for the alternative variables described in the text.

We present in table 1 the results of the direct estimation of equation 8 and several variants of it. We begin in equation 1-1 with the basic model. All coefficients have the expected signs. All independent variables are statistically significant (on one-tailed tests), with six variables at 1 percent, two at 5 percent, and one, Δg , at 10 percent. The variance explained by the model is quite high given its focus on changes in

aggregate productivity (rather than levels), and the Durbin-Watson statistic allows us to accept the null hypothesis of zero autocorrelation.

The second column presents results for the same model with e , the effectiveness of employer control, decomposed into its three constituent variables. The model remains robust, with virtually no change in the coefficients on the other significant independent variables. The cost-of-job-loss component of e , the variable j , is highly significant and clearly constitutes the underlying component of e with the greatest explanatory power; its standardized regression coefficient is actually higher than the standardized regression coefficient for e in equation 1-1. The coefficient on d also has the right sign, but otherwise performs poorly. The coefficient for s , the rate of change of the intensity of supervision, is statistically insignificant.

We present in the column for 1-3 the results of equation 8 estimated with only j included as a measure of variations in e . As in equation 1-2, j is positive and significant, with a coefficient near to the value for e reported in 1-1, and the results for the other variables remain consistent.

Given the essential equivalence of the results in 1-1, 1-2, and 1-3, we choose to work with the simpler version presented in equation 1-3. Although we believe that the version in 1-1, with the fully specified variable e , represents the theoretically correct representation of the microeconomic logic of our analysis of the effectiveness of employer control, we retain the version in 1-3 for subsequent statistical analysis to avoid the possibility that some other components of e with less powerful statistical effects might complicate these comparative and forecasting exercises.⁵⁰

We turn next to our proxy measure for innovative pressure on

50. See Bowles, "Competitive Wage Determination," for further theoretical justification for the use of J , our measure of the cost of job loss.

Some readers of an early draft have expressed concern about a possible identity in the relation between Q and J in our model because the expression for J includes the wage rate and there is a close relation between the rates of change of productivity and the product wage (see equation 6). This concern is misplaced, however, because W appears in both the numerator and the denominator of J . If the other determinants of J were constant and small, J would fluctuate around a value of 1.00, rather than around the value of W . In fact, variations in J are dominated by variations in our measures of unemployment duration, income-replacing payments, and nonincome-replacing payments, not by changes in either the product wage or in our measure of real spendable hourly earnings. Indeed, the simple correlation coefficient between the rate of change of the product wage and J is actually negative.

business. Assuming for the moment that the business-failure rate constitutes the appropriate basis for such a measure, we test several alternative specifications of this variable. We report in 1-4 the results with a simple alternative specification, C' , a nonresidualized, three-year moving average of the business-failure rate. The magnitude of the coefficients for C^* and C' differ because the residualization shifts the units of measurement on C^* , but the standardized regression coefficients are almost exactly equal and so are their levels of statistical significance. This suggests, in other words, that our results are insensitive to the choice about whether or not to adjust the business-failure rate for its cyclical covariation with the capacity utilization rate; we prefer such an adjustment to focus attention on longer-term trends in innovative pressure. We also test a five-year moving average of the business-failure rate and a specification in which we treat the current value of this rate as a two-year autoregressive distributed lag on past values of the same rate—an alternative measure of the notion of cumulative trends in innovative pressure. Both of these specifications, not reported here, yielded equivalent results on both the innovative pressure variable and on the other independent variables in the model.⁵¹

We consider next our specification of the variable measuring relative external input prices. Equation 1-5 reveals the results of substituting p_f , the variable measuring relative fuel prices, for p_x . Although its coefficient has the right sign, it is quite small and statistically insignificant. If, as we and many other economists suspect, movements in one or another component of external input prices have dampened productivity growth since the mid-1960s, our measure of relative nonagricultural crude-materials prices appears to capture this effect more adequately than the narrower measure of relative fuel prices.

51. We also explored a definition of the variable based on net business formations, taking into account not only failures but new enterprises. The problem with additional attention to new enterprise formation, however, is that it is almost entirely a function of real interest rates and appears to have little connection with other dimensions of macroeconomic activity. The frequency of net business formations grew steadily during the postwar period, particularly during the years of low real interest rates in the 1970s, and does not appear to have moved in close relation to other factors likely to affect aggregate productivity. Failures and net business formations, indeed, move in opposite directions; the simple correlation between the frequency of business failures and net formations is -0.47 . We therefore think that the failure rate more closely reflects the underlying factors that affect relative success at modernization and innovation.

The two other “social” variables, $\Delta w!$ and z , also deserve further comment. Although productivity growth and wage growth are closely linked, the introduction of $\Delta w!$, one of our indicators of worker motivation, should not introduce simultaneous equation bias into our equation because it relates the *level* of worker motivation (and therefore the level of work intensity and of aggregate labor productivity) to the *rate of change* in workers’ take-home pay in equation 8. There is no necessary statistical relation between the first and second derivatives of a variable, so there is no a priori reason to treat $\Delta w!$ as an endogenous variable and to expect simultaneous equation bias as a result of its inclusion in 8. The simple correlation coefficient between q and $\Delta w!$ is only 0.37, barely more than half the simple correlation between q and $w!$, the first derivative of real spendable hourly earnings.

The results reported for equation 1-3 may still reflect causality running from the rate of growth of productivity to the rate of growth of real wages (and therefore, if even indirectly, $\Delta w!$). We can test for this possibility by residualizing $\Delta w!$ on the rate of growth of the product wage (hourly compensation deflated by the GDP deflator) and then including that residualized variable, $\Delta w!^*$, in 8. (This residualization allows us to eliminate the portion of variations in $\Delta w!$ that are plausibly understood as endogenously determined along with q .) We present the results of this procedure in equation 1-6, in which we substitute the residualized independent variable $\Delta w!^*$ for $\Delta w!$. There is some decrease in the coefficient and statistical significance of this measure of our motivational hypothesis, but the variable remains significant at 10 percent and the rest of the results remain robust. (There is little change in the results largely because the simple correlation between $\Delta w!$ and rate of change of the product wage is only 0.36.)⁵²

We would obviously have preferred a measure of the quality of working conditions that covers the entire nonfarm private sector rather than just the industrial accident rate, z . Lacking such a series, we are reasonably confident that trends in manufacturing closely paralleled trends in other sectors. During the period when industrial accident rates

52. We further estimated Phillips curve relations with $w!$ and $\Delta w!$, respectively, as dependent variables, and the lagged unemployment rate and productivity growth, among others, as independent variables. While such a model explains a large portion of annual variation in $w!$ —the rate of growth of our measure of real spendable earnings—it explains only 10 percent of the annual variation in $\Delta w!$ (adjusted for degrees of freedom).

began to rise after the mid-1960s, for example, there was both rising job dissatisfaction and increasing concern about working conditions among the workers in white-collar occupations.⁵³

There is one final test of the adequacy of $\Delta w!$ and z as measures of factors affecting worker motivation. As noted at the beginning of this paper, one consistent data series on employee satisfaction is available since the mid-1950s; there are six observations on this series over the period of our analysis (see note 7). Despite the limited degrees of freedom, our two proxy variables should certainly help explain variations in the intermittent variable measuring job satisfaction. When we regress $M!$, this measure of job satisfaction, on $W!$ and Z , indeed, the two proxy variables have the expected signs and explain 65 percent of the variation in $M!$. We can further use the coefficients from this regression to generate an annual series of predicted job satisfaction based on the annual values for $w!$ and Z . Equation 1-7 shows the results of substituting the rate of change of this measure of predicted job satisfaction for $\Delta w!$ and z in equation 1-3. The coefficient on $m!$ is statistically significant and all the other results remain robust. This further strengthens the conclusion that the effects of $\Delta w!$ and z in equations 1-1 through 1-3 capture to a large degree the effects of shifts in factors affecting worker motivation. We retain those variables for subsequent analysis, rather than our measure of predicted job satisfaction, because the coefficients generating that measure are based on only six observations.

The three columns of table 2 provide tests of the sensitivity of the results to the specification of the dependent variable. Equation 2-1 replicates 1-3, except that *total* employee hours, rather than production-worker hours, are in the denominator of productivity, the dependent variable (and, maintaining consistency, in the index of k_u , the ratio of utilized capital to labor). The model remains robust, with no significant changes in coefficient magnitude or significance between 1-3 and 2-1.

The results of decomposing the dependent variable specified in equation 8 appear in equation 2-2. The dependent variable in 2-2 is y , the change in output in the nonfarm private business sector; and the change in production-worker employment, l_p , is added to the right-hand side as an additional independent variable. We also convert the measure of

53. See *Quality of Work Life* (Institute for Social Research, University of Michigan, 1979); and the summaries in Staines, "Is Worker Dissatisfaction Rising?"

Table 2. Alternative Dependent Variables in the Social Model of Productivity Growth in U.S. Nonfarm Private Business, 1948–79^a

Independent variable	Equation		
	2-1	2-2	2-3
λ^*	0.014 (7.78)	0.026 (4.97)	0.016 (8.09)
g	0.481 (4.84)	0.799 (4.09)	. . .
Δg	0.091 (1.61)	0.056 (1.05)	0.120 (4.31)
k_u	0.417 ^b (4.69)	0.143 ^b (0.92)	0.427 (5.11)
j	0.033 (3.52)	0.024 (2.38)	0.028 (4.77)
$\Delta w!$	0.080 (1.74)	0.089 (2.06)	0.064 (1.47)
z	-0.079 (-3.25)	-0.068 (-2.81)	-0.083 (-3.55)
p_x	-0.037 (-1.91)	-0.022 (-1.10)	-0.040 (-2.12)
C^*	0.011 (2.64)	0.012 (3.17)	0.010 (2.67)
l_p	. . .	0.619 (3.28)	. . .
Summary statistic			
$\bar{R}^2$	0.917	0.983	0.899
Standard error of estimate	0.005	0.004	0.005
Durbin-Watson	2.254	2.402	2.142

Source: Authors' estimates based on data cited in the appendix.

a. The dependent variable in 2-1 is the rate of change of output per total-employee hour; in 2-2, the rate of change of output; and in 2-3, the rate of change of production-worker hourly output residualized on the rate of change of capacity utilization. The variable l_p is rate of change in production-worker hours. Given first differences, actual years of observation are 1949–79. The numbers in parentheses are *t*-statistics.

b. Adjusted to correspond with the redefinition of the dependent variable, as described in the text.

capital intensity to a direct measure of the rate of change of the utilized capital stock by removing labor hours from the denominator. The R^2 is naturally higher in 2-2 than in 1-3.⁵⁴ Otherwise the model is relatively insensitive to this change in the form of specification of the dependent variable: the social variables are robust, although j falls slightly in magnitude of coefficient and statistical significance; the technical variables are the ones, interestingly, that shift substantially with this re-

54. The results in 2-1 are roughly consistent with the assumption of constant returns to scale implied in the initial specification of equations 4 and 5, for the coefficient on l_p is close to the share of production workers' compensation in nonfarm business income.

specification, inasmuch as the coefficients on g , k_u , and p_x all change greatly.

Because many of the variables included in the model vary over the business cycle, it seems important to test the sensitivity of our results thus far by using a dependent variable that is itself cyclically adjusted. We computed such a variable by first regressing q , the rate of change of productivity, on g , the rate of change of capacity utilization, and then taking the residual from that equation as our measure of decyclical productivity growth. We then regressed this measure of residualized productivity growth on all variables in equation 8 with the obvious exception of g itself. We report these results in equation 2-3.⁵⁵ Given the possibilities of cyclical covariation among many of the independent variables, the results are surprisingly robust. The R^2 remains high. Only Δg , the change in the rate of change of capacity utilization, is dramatically affected by moving to the decyclical dependent variable, with its coefficient increasing in both magnitude and significance.

COMPARATIVE PERFORMANCE

We retain the decyclical specification in 2-3 for the purposes of comparative tests of the model's explanatory power and structural stability. Table 3 compares our results with those that might be extracted from prevailing discussions of the productivity slowdown. Equation 3-1 reproduces the model as reported in 2-3. Equation 3-2 estimates the simplest possible technical model that can be derived from the available mainstream literature; it includes Δg to control for sluggish firm adjustments to changes in the level of business activity; k_u , the change in the utilized capital-labor ratio, reflecting the concern of the mainstream

55. There are a variety of ways of performing this residualization; one can work from either equation 4 or 5, which have comparable results. Two features of the decyclical model in 2-3 are worth noting in this regard. First, the fact that the effects of j remain robust even after the dependent variable has been residualized on g suggests that its effects are not simply an additional variable reflecting the cycle. Second, we have tested for the relative importance of the two main components of J in equation 6: unemployment duration and relative income loss. When we reestimate 2-3 with the rates of change of those two components substituted for j , both component variables are statistically significant, although the standardized regression coefficient on the unemployment-duration component is the larger of the two. All other results remain essentially unchanged with this decomposition.

Table 3. Alternative Models of Aggregate Productivity Growth in U.S. Nonfarm Private Business, 1948–79^a

Independent variable	Equation			
	3-1	3-2	3-3	3-4
λ^*	0.016 (8.09)	0.009 (2.12)	0.011 (2.50)	0.015 (7.09)
Δg	0.120 (4.31)	0.048 (0.91)	0.066 (1.25)	0.114 (3.74)
k_u	0.427 (5.11)	0.758 (4.57)	0.771 (4.50)	0.469 (5.39)
j	0.028 (4.77)	...	...	0.028 (4.72)
$\Delta w^!$	0.064 (1.47)	...	...	0.075 (1.67)
z	-0.083 (-3.55)	...	...	-0.076 (-2.73)
p_x	-0.040 (-2.12)	...	...	-0.039 (-2.04)
C^*	0.010 (2.67)	...	...	0.011 (2.49)
p_f	...	-0.037 (-1.06)	0.028 (0.48)	...
<i>Dummy</i> ₁₉₆₇₋₇₃	...	...	-0.009 (-1.82)	-0.002 (-1.04)
<i>Dummy</i> ₁₉₇₄₋₇₉	...	...	-0.011 (-1.21)	0.001 (0.25)
Summary statistic				
$\bar{R}^2$	0.899	0.485	0.512	0.899
Standard error of estimate	0.005	0.010	0.010	0.005
Durbin-Watson	2.142	1.517	1.767	2.257

Source: Authors' estimates based on sources cited in the appendix.

a. The dependent variable is the logarithmic rate of change in output per production-worker hour residualized on the logarithmic rate of change in capacity utilization. The variable p_f denotes the rate of change in relative fuel prices. Given first differences, the actual years of observation are 1949–79. The numbers in parentheses are *t*-statistics.

literature with capital intensity and the hypothesis of capital shortage; and p_f , the measure of relative input prices that seems to reflect the hypotheses of recent discussions about the oil-price shock most closely. We consider elaborations and extensions of this simple formulation of the technical model in the following section, with particular attention to the effects of changes in characteristics of the labor force.

Several conclusions flow from the comparison of the results in equations 3-1 and 3-2. First, this kind of “technical” model that excludes our social variables neither explains as much of the annual variation in

(decyclized) productivity growth nor remains as free of potential inefficiency from autocorrelation as the more inclusive model reported in 3-1. Second, such a technical model generates substantially higher estimates of the impact of variations in utilized capital intensity on productivity; assuming, on both theoretical and econometric grounds, that the social model is a more fully specified equation, this suggests that conventional studies have suffered from underspecification bias and have substantially overestimated the impact of slowdowns in the rate of growth of the capital-labor ratio. Third, p_f is statistically insignificant even in the more limited technical model and appears again as a more statistically imprecise measure of effects of external input prices.

There is another useful way to assess econometrically the ability of these alternative models to account for period-specific declines in the rate of productivity growth. As the data in the display above report, the rate of growth of output per production-worker hour slowed by 0.68 percentage points from 1948–66 to 1966–73 and by 2.02 points from 1948–66 to 1973–79. The corresponding decrements for the decyclized measure of productivity growth we use, the dependent variable in 3-1 and 3-2, were 0.69 and 1.76 percentage points, respectively. We can test for the ability of these two models to capture these between-period declines by adding dummy variables for the years between 1967 and 1973 and between 1974 and 1979. If the other independent variables account not only for annual variations in productivity growth but also for average between-period declines, the estimated coefficients on these respective dummy variables should be statistically insignificant and close to zero. If, on the other hand, one or another of the models could account for little of a specific between-period decline, the estimated coefficient on that dummy variable would be close to the values of -0.0069 or -0.0176 and, presumably, statistically significant.

Equations 3-3 and 3-4 show results of this test for the two models. In 3-3, the results for the technical model, the 1967–73 dummy variable is statistically significant at 5 percent and is actually greater than the between-period difference in productivity growth rates; this confirms a familiar result in conventional studies of the slowdown from 1966 to 1973—that is, capital intensity grew very rapidly during this period, and technical factors are unable to account for any of the first phase of slower productivity growth between 1966 and 1973. The estimated coefficient on the second dummy variable in 3-3 falls just below a 10

percent level of significance and is equal to roughly three-fifths of the overall decline in productivity growth from 1948–66 to 1974–79, further confirming the recent conclusions of Bosworth and many others that slower capital formation in the 1970s explains relatively little of the productivity slowdown in those years.⁵⁶

Equation 3-4 suggests, in contrast, that the basic social model presented in 3-1 can account statistically for virtually all between-period productivity slowdowns; neither dummy variable reported in 3-4 is statistically significant, and both are quite small.

What factors in that model play the greatest (estimated) role in accounting for the slowdown itself? We can provide direct statistical estimates of the relative explanatory power of the different constituent variables represented in equation 8. Relying on the general algebraic result, in matrix notation, $\Delta\hat{y} = \hat{\beta}\Delta X$, we can estimate the predicted change in q between the various phases of the postwar period that we expect to result from the movements in the respective independent variables using coefficients calculated in the basic estimation of equation 8. We present this comparison in table 4; there we account for the decline in q from the 1948–66 boom years to the 1966–73 phase of slowdown and then again for the decline in growth rates from 1948–66 to 1973–79. We make use of the complete version of the model reported in equation 1-3, rather than the decyclicized version in 2-3, in order to take account of differences in the rate of change of capacity utilization from the period of prosperity to the successive periods of slowdown.

The first and third columns present the predicted percentage points of decline in hourly productivity growth, while the second and fourth columns report the percentage of the total predicted decline that is attributable to each of the variables. For explaining the decline from 1948–66 to 1973–79 we use the coefficients reported in column 1-3. For the decline from 1948–66 to 1966–73 we use coefficients for the comparable equation estimated from the shorter period from 1948 to 1973. Further to clarify the relative contributions of different variables we provide subtotals by the major categories of factors stipulated in the original presentation of the social model of productivity growth.⁵⁷

56. See Bosworth, "Capital Formation and Economic Policy."

57. The procedure applied in table 4 would not be valid if a significant number of the variables incorporated in the calculations were statistically insignificant; since we are relying only on variables that prove to be statistically significant in column 1-3, our use of

Table 4. Accounting for the Productivity Slowdown, Selected Periods, 1948–79^a

Variable	Attribution of decline in productivity growth			
	1948–66 to 1966–73		1948–66 to 1973–79	
	Percentage points of decline in q	Share of the decline (percent)	Percentage points of decline in q	Share of the decline (percent)
$g, \Delta g$	0.13	23	0.34	16
k_u	–0.12	–21	0.53	25
$e, z, \Delta w!$	0.57	98	0.60	28
p_x	0.07	12	0.35	16
C^*	–0.07	–12	0.32	15
Total predicted decline	0.58	100.0	2.14	100.0
Actual decline	0.68	...	2.02	...

Source: Authors' calculations.

a. Percentage points of predicted decline in productivity growth, q , are calculated by multiplying the regression coefficients from the basic model of equation 8 by the decline in the average values for the respective independent variables for two periods being compared in the two parts of the table. The comparison of the decline from 1948–66 to 1973–79 is based on the coefficients reported in equation 1-3. The comparison between 1948–66 and 1966–73 is based on the comparable coefficients estimated for the period from 1948 to 1973.

Table 4 shows once again that the estimated social model can account for essentially all the actual decline in q in each of the two critical phases of the slowdown. We conclude, as much as one can rely on statistical estimations of this sort, that the social model of aggregate productivity growth has “solved the puzzle” of the productivity slowdown.

In the first phase of decline the movements of capacity utilization and capital intensity, the core variables in traditional analyses of aggregate productivity growth, are unable to account for any of the slowdown in productivity growth, and both variables predict a decline of only 0.01 percentage points in productivity growth between 1948–66 and 1966–73; this is due to the significant increase in the growth rate of the utilized capital-labor ratio in 1966–73. Among the variables introduced in this discussion of the social dimensions of productivity, those measuring changes in factors affecting work intensity account for by far the largest

unadjusted regression coefficients is appropriate. We calculate the proportionate influence of our vector of explanatory variables as a percentage of total predicted decline, rather than actual decline, to maintain internal consistency within the calculations.

The results reported in equation 1-3 of table 1 and in table 4 differ slightly from the results reported in chap. 6 and app. C of our book, *Beyond the Waste Land*. The results reported here supersede those in our book, since they are based on an improved specification of the basic model and some data revisions that we were unable to incorporate into the versions reported in our book.

share of the first period of slowdown, more than 98 percent of the predicted decline. This lends credence statistically to what we have already suggested historically—that work intensity declined rapidly after 1966 and that corporations were not capable of restoring work intensity in the years before 1973.⁵⁸

The second phase of decline suggests a pattern that is quite different, one with each of the five categories of variables accounting for a significant portion of the total predicted decline; the variables affecting work intensity remain the most important in accounting for the slowdown.⁵⁹

One final test of the statistical properties of the basic social model is in some ways the most demanding and the most important. Many mainstream analyses of the productivity slowdown conclude that its mysteries result from exogenous structural changes distorting the economy's normal mechanisms generating steady expansion. This conclusion implies that models explaining productivity growth would be incapable of accounting *endogenously* for the productivity slowdown and that recourse to external factors would be necessary to explain changes in the performance of the economy, particularly after 1973.

Our historical analysis leads us to an opposite conclusion. We argue that the structural forces that provided the basis for postwar prosperity also led to the stagnation of the late 1960s and 1970s; that is, the structure of postwar prosperity itself eventually generated declining productivity growth.

This conclusion can be tested through an ex post forecasting exercise. If we are correct in our hypotheses about structural stability, the social model, as estimated in either its basic or decyclicized versions, should do as well in explaining productivity growth during the period of prosperity as it does during the two periods of slowdown. More pertinently, it should be possible to explain the productivity slowdowns after 1966 and 1973 by means of an ex post forecast with structural coefficients estimated for the years leading up to 1966 and 1973, respectively.

Tables 5 and 6 and the following paragraphs present the results of

58. See Bowles, Gordon, and Weisskopf, *Beyond the Waste Land*, chaps. 4–5.

59. Ibid. We provide there an additional argument about the feedback of policies to restore work intensity on declining capacity utilization and slower growth in capital intensity; we call it the “cold bath effect” and present some econometric evidence for those connections in appendix C of the book.

Table 5. Structural Stability Tests, Selected Periods, 1948–79^a

Independent variable	Social model			Technical model		
	1948–79 3-1	1948–73 5-1	1948–66 5-2	1948–79 3-2	1948–73 5-3	1948–66 5-4
λ^*	0.016 (8.09)	0.015 (5.62)	0.017 (5.56)	0.009 (2.12)	0.014 (2.97)	0.017 (2.96)
Δg	0.120 (4.31)	0.114 (2.90)	0.038 (0.69)	0.048 (0.91)	0.022 (0.39)	0.009 (0.14)
k_u	0.427 (5.11)	0.440 (4.24)	0.439 (3.56)	0.758 (4.57)	0.543 (2.91)	0.519 (2.17)
j	0.028 (4.77)	0.027 (4.15)	0.039 (5.63)	...	...	...
$\Delta w^!$	0.064 (1.47)	0.054 (1.10)	0.117 (2.07)	...	...	...
z	-0.083 (-3.55)	-0.103 (-2.73)	-0.033 (-0.71)	...	...	...
p_x	-0.040 (-2.12)	-0.018 (-0.47)	-0.018 (-0.35)	...	...	...
C^*	0.010 (2.67)	0.013 (1.98)	0.008 (1.21)	...	...	...
p_f	...	...	...	-0.037 (-1.06)	-0.031 (-0.51)	-0.003 (-0.03)
Summary statistic						
$\bar{R}^2$	0.899	0.799	0.812	0.485	0.203	0.120
Standard error of estimate	0.005	0.005	0.005	0.010	0.010	0.010
Durbin-Watson	2.142	2.188	2.367	1.517	1.802	2.027

Source: Authors' estimates based on data cited in the appendix.

a. The social model and the technical model are estimated based on three successive periods reproducing the model structure from 3-1 and 3-2, respectively. The dependent variable is q^* , the decyclical rate of growth of hourly output. The numbers in parentheses are t -statistics.

such an exercise. As in the analysis of comparative explanatory power above, we use the decyclical model, denoting the decyclical dependent variable as q^* , and present evidence comparing both the structural stability and forecasting performance of the social and technical models represented by 3-1 and 3-2.

Columns 5-1 and 5-2 present the results of estimation of the social model for two different periods of estimation: first for the longer period from 1948 to 1973 and then for the more demanding and shorter period from 1948 to 1966. (The first column reproduces the coefficients from 3-1 of table 3 for ease of comparison.) Particularly for the period of estimation from 1948 to 1973, but even for the shorter period from 1948 to 1966, the results suggest substantial comparability between the full

Table 6. Ex Post Forecasts of Aggregate Productivity Growth, Selected Periods, 1967–79^a

Independent variable	Social model		Technical model	
	1974–79 6-1	1967–79 6-2	1974–79 6-3	1967–79 6-4
Constant	0.0002 (0.13)	0.007 (3.02)	0.012 (9.61)	0.019 (11.83)
q^*	0.841 (10.21)	0.857 (8.11)	0.314 (5.33)	0.371 (5.25)
Summary statistic				
$\bar{R}^2$	0.954	0.844	0.846	0.689
Standard error of estimate	0.004	0.006	0.003	0.004
Durbin-Watson	1.272	1.778	1.541	1.171

Source: Authors' estimates based on data cited in the appendix.

a. The dependent variable is predicted q^* , the out-of-sample forecast for equations from columns 5-1 and 5-2, 5-3 and 5-4, respectively. The numbers in parentheses are t -statistics.

and shorter periods of estimation. The signs and magnitudes of the coefficients are quite close and the regression statistics are also similar. Three variables, z , p_x , and C^* , have small and insignificant coefficients for the shortest period, but these variables themselves display relatively little variation during the period of prosperity.⁶⁰ The fact that this model still explains 81 percent of the variation in productivity growth, adjusted for degrees of freedom, without taking into account information about the periods of slowdown after 1966 and 1973 suggests that the model's explanatory power is not dependent on specific or exogenous postprosperity developments.⁶¹

Columns 3-2, 5-3, and 5-4 present parallel data for the technical model. That model fares less well when estimated for the shorter periods, with

60. It is also interesting to note that both j and $\Delta w!$ are highly significant in the estimation for 1949–66, lending support to the analysis developed in *Beyond the Waste Land* that rapid productivity growth in the postwar boom depended heavily on the stimulus effects of a rising cost of job loss and the incentive effects of rapid growth in workers' take-home pay.

61. It is possible to conduct more formal statistical tests for the structural stability of the equations by conducting a Chow test for the equality of the coefficients of the estimated equations for the respective periods of estimation. Two pair-wise tests are possible: 1948–66 versus 1966–79; and 1948–73 versus 1973–79. The latter is inappropriate for the social model because there are insufficient degrees of freedom to estimate the full equation during the 1973–79 period. For the former case, the relevant F -statistic falls substantially below the critical value (at 5 percent) for that comparison, allowing us to accept the null hypothesis of equivalent coefficients.

a significant drop in its adjusted coefficient of determination and a notable decline in the estimated magnitude of the coefficient for k_u .⁶²

Below we use the respective period-of-estimation coefficients to generate average annual predicted rates of productivity growth for 1966–79 and 1973–79 and compare them with the actual average rates of change in the decyclicalized dependent variable for those years. With the

	<i>Average annual rate of productivity growth (percent)⁶³</i>	
	<i>1973–79</i>	<i>1966–79</i>
Actual q^*	1.036	1.669
Social model, $\hat{q}^*$	0.894	2.164
Technical model, $\hat{q}^*$	1.526	2.546

1948–73 estimation, for example, the social model forecasts an average annual predicted rate of productivity growth for 1973–79 of 0.89 percent, which is very close to the actual rate; the technical model generates an average annual predicted rate of 1.53 percent, roughly 50 percent higher than the actual rate. Although the predictions from our forecasts, not surprisingly, are less accurate based on the shorter 1948–66 period of estimation, the social model nonetheless outperforms the more limited technical model by a comparable margin.

The above results for average forecast performance ignore the closeness of fit from year to year. Table 6 provides the basis for the latter comparison by regressing out-of-sample predicted values for q^* from the appropriate equations in table 5 against the actual values for q^* for 1974–79 and 1967–79, respectively. A perfect forecast performance, obviously, would result in an estimated regression coefficient of 1.00 and an R^2 of 1.00.

62. The coefficient on the k_u variable in the equations for 1949–73 and 1949–66 equations 5-3 and 5-4 falls to a value close to its stable levels in the estimations with the social model, suggesting that its higher estimated values in the 1949–79 estimations of the technical model are due to the artificially high weight placed on declining rates of capital formation in 1974–79 in the underspecified technical model; it attributes to declining rates of growth of capital intensity some of what is explained by the social variables in our more inclusive social model.

63. The predicted values for q^* are calculated with the period-of-estimation coefficients from equations 5-2 and 5-4 for the 1966–79 estimates and from 5-1 and 5-3 for the 1973–79 estimates.

Equations 6-1 and 6-2 report these forecast results for the social model, providing substantial support for our conclusions of structural stability. The forecast for 1974–79, based on coefficients for 1948–73, is particularly successful: the estimated coefficient is 0.841; the $\bar{R}^2$ is 0.95; and we reject, by the appropriate test [$t = (\hat{\beta} - 1.00)/\hat{\sigma}_{\hat{\beta}}$], the alternative hypothesis that $\hat{\beta}$ is statistically different from 1.00 at the 95 percent confidence level. The forecast results for 1967–79, based on coefficients estimated for 1948–66, are only slightly less impressive, with a comparable value for $\hat{\beta}$ and the $\bar{R}^2$ almost as large.

Subjected to the same tests, the technical model exhibits less successful forecasting characteristics: the estimated magnitudes of the regression coefficients are substantially lower; the adjusted coefficients of determination are also lower; and the forecast performance depends much more on the constant term than in the case of the social model.

It appears, in short, that the social model provides a robust and comprehensive statistical explanation of the slowdown in aggregate productivity growth in the U.S. economy after 1966.

Extensions and Competing Hypotheses

However successful, the basic social model developed and tested in the two preceding sections represents a very provisional effort to encompass some social determinants of aggregate productivity growth that have been ignored in mainstream analyses. We explore in this section alternative hypotheses advanced in the productivity literature. We show that this basic model remains robust in the sense that its explanatory power is not undercut when confronted with alternative (or competing) explanations.

We follow a standard procedure throughout this section: after specifying a string of additional variables identified by alternative hypotheses, we first consider the effects of adding those variables to the technical model, with the decyclicalized dependent variable as reported in 3-2, and then look at the effects of adding them to the apparently more complete social model as reported in 3-1. Any of the additional variables whose sign is consistent with theoretical expectations and whose inclusion in the more complete social model is warranted on econometric grounds will then be carried over to a round of estimation after each of these

separate tests. As before, we introduce variables in the text as levels for ease of exposition and then translate them into rates of change for the purposes of econometric estimation.⁶⁴

LABOR FORCE COMPOSITION AND QUALITY

Some have attributed a significant portion of the decline in productivity growth rates to changes in composition of the labor force and declining "quality" of the employed population. Although several dimensions of this possible effect have been explored, most analysts have concentrated on the ostensible impact on quality of the rising proportion in the labor force of women and younger workers.⁶⁵

A problem with most of these studies, however, is that they have axiomatically applied the marginal productivity theory of wages. Demographically adjusted indexes of labor input are derived by assuming that the relative productivity, or labor "quality," of different age-sex labor force groupings is captured by the relative wages. We are skeptical about both the validity of and the necessity for the use of wages as proxies for productivity.⁶⁶ Hypotheses about the effects of changing labor force composition on productivity can and should be tested directly, not presumed. We consider here three main hypotheses about how education, age composition, and sex composition affect labor force quality.

As Denison and others have noted, the educational attainment of the labor force has risen fairly steadily over the entire postwar period, so

64. We require that a variable at least increase the adjusted coefficient of multiple determination in the social model, with the correct sign, for inclusion in the final round of estimation. This criterion is properly applied only when inclusion or exclusion of the variable involved does not otherwise substantially affect the coefficients on the other independent variables. For one useful discussion of this problem of specification, see Potluri Rao and Roger LeRoy Miller, *Applied Econometrics* (Wadsworth, 1971), pp. 35–38.

65. For two of the most systematic discussions of these effects, see George L. Perry, "Labor Force Structure, Potential Output, and Productivity," *BPEA*, 3:1971, pp. 533–65; and Jeffrey M. Perloff and Michael L. Wachter, "The Productivity Slowdown: A Labor Problem?" in Federal Reserve Bank of Boston, *The Decline in Productivity Growth*, pp. 115–42.

66. For a useful recent summary of problems with interpreting demographic wage differentials as indicators of differences in productivity, particularly by race and by sex, see Donald J. Treiman and Heidi I. Hartmann, eds., *Women, Work, and Wages: Equal Pay for Jobs of Equal Value* (National Academy Press, 1981), chaps. 2–3.

that variations in its movements are unlikely to account for variations in the growth of aggregate productivity.⁶⁷ But this presumption should be tested like any other. We can measure changes in the educational "quality" of the labor force at least approximately by a variable measuring changes in the median educational attainment of the labor force; this variable is denoted v .

Equation 7-1 in table 7 reports on the addition of v to the technical model. Its coefficient is significant and positive, as expected. When added to the social model in equation 7-2, however, the coefficient falls to one-third its level in 7-1 and is no longer significant even at 10 percent. Since its inclusion nonetheless slightly raises the adjusted R^2 , it becomes a candidate for inclusion in the final round of estimation.

It is also possible to test directly for the effects of the age and sex composition of the labor force. Some have argued that relatively younger workers have lowered the average experience of the labor force, reducing the general skill levels of the employed and thereby retarding productivity growth. We test this effect by adding a variable for labor force inexperience, which we express as L_y , the percentage of the labor force between sixteen and twenty-four years old; this measure of "inexperience" rose significantly after the early 1960s. Others have argued a similar hypothesis about the share of women in the labor force, assuming that women have relatively lower skills than men and that their rising share of total employment has similarly retarded productivity growth. We test this hypothesis by including a variable for the female-employment share, which we express as L_f , the percentage of total nonfarm private employment that is female.

In equations 7-3 and 7-4 we report the results of adding these two variables to the technical model. The proxy for inexperience, l_y , is insignificant, while l_f has the correct sign and is statistically significant. When each variable is added to the social model in 7-5 and 7-6, however, neither is significant and each reduces the adjusted R^2 .

To check for potential complementarities among these three measures of labor force characteristics, we include all of them in the final two columns of table 7. The results of their inclusion remain consistent: when added to the technical model, both the proxy for education and the female-employment share have the correct signs and are significant. When added to the social model in 7-8, neither the variables for

67. See Edward F. Denison, "Explanations of Declining Productivity Growth," *Survey of Current Business*, vol. 59 (August 1979), pp. 2-3.

Table 7. Productivity Growth and Labor Supply Characteristics, 1948–79^a

Independent variable	7-1	7-2	7-3	7-4	7-5	7-6	7-7	7-8
λ^*	0.004 (0.92)	0.013 (4.94)	0.009 (2.09)	0.013 (2.91)	0.016 (7.89)	0.016 (7.41)	0.007 (1.32)	0.013 (4.00)
Δg	0.083 (1.61)	0.104 (3.46)	0.051 (0.94)	0.014 (0.27)	0.119 (4.19)	0.118 (3.89)	0.052 (1.00)	0.100 (3.03)
k_u	0.753 (4.88)	0.450 (5.34)	0.762 (4.51)	0.844 (5.18)	0.427 (5.00)	0.434 (4.60)	0.817 (5.29)	0.465 (4.79)
j	...	0.029 (4.99)	...	...	0.028 (4.46)	0.028 (4.59)	...	0.028 (4.43)
$\Delta w!$	...	0.095 (1.93)	...	...	0.064 (1.43)	0.062 (1.37)	...	0.099 (1.88)
z	...	-0.053 (-1.64)	...	...	-0.083 (-3.28)	-0.082 (-3.40)	...	-0.050 (-1.48)
p_f or p_x	-0.003 (-0.09)	-0.033 (-1.72)	-0.035 (-0.97)	-0.036 (-1.07)	-0.40 (-2.05)	-0.040 (-2.08)	-0.002 (-0.44)	-0.034 (-1.67)
C^*	...	0.010 (2.92)	...	...	0.010 (2.13)	0.010 (2.32)	...	0.008 (1.45)
v	0.730 (2.27)	0.301 (1.28)	...	...	...	...	0.849 (2.25)	0.386 (1.39)
l_y	...	...	-0.021 (-0.33)	...	-0.001 (-0.02)	...	0.051 (0.76)	0.029 (0.65)
l_f	...	...	...	-0.526 (-2.01)	...	-0.026 (-0.18)	-0.447 (-1.78)	-0.023 (-0.16)
Summary statistic								
$\bar{R}^2$	0.554	0.902	0.467	0.537	0.894	0.894	0.592	0.894
Standard error of estimate	0.010	0.005	0.011	0.010	0.005	0.005	0.009	0.005
Durbin-Watson	1.647	2.090	1.526	1.609	2.143	2.149	1.794	2.083

Source: Authors' estimates based on data cited in the appendix.

a. The dependent variable is the decyclical rate of change of hourly output, q^* . The variable v is rate of change in the educational attainment of the labor force; l_y , the rate of change in the labor force aged sixteen to twenty-four; and l_f , the rate of change in the female share of employment. Given first differences, actual years of observation are 1949–79. The numbers in parentheses are t -statistics. The input-price variable is entered as p_f in the technical model and p_x in the social model.

inexperience nor for female-employment share is significant while the proxy for education is now significant at 10 percent. Based on these results, we carry over v for use in final estimation.⁶⁸

ADDITIONAL FACTORS OF PRODUCTION

Some analysts have focused on the effects on productivity growth of additional factors of production, exploring the impact of variations in

68. These results confirm our concern about the possible biases in conventional accounting-method studies of the productivity slowdown. See note 46 and the corresponding discussion in the text.

energy consumption, supervisory inputs, or both. Theory might lead one to expect that productivity would be positively related to the ratio of energy consumption to production-worker hours and also positively related to the ratio of nonproduction (or supervisory) employment to production-worker employment, particularly with our definition of a dependent variable as output per production-worker hour. We have tested these two hypotheses about additional "factors" of production by adding variables to our basic model measuring X , the ratio of physical energy units (in Btu units consumed by industry) to production-worker hours; and S , the intensity of supervision as defined above. Neither variable is statistically significant in either specification. Given that we had already taken into account the relative price of external inputs, p_x , it is not surprising that adding a measure of the energy-labor ratio did not improve the explanatory power of our model. But even in a separate equation from which p_x was excluded, x was not significant. And given what we have already observed in column 1-2, it is also not surprising that the addition of a measure of the intensity of supervision as a direct factor of production did not affect the results.

SECTORAL COMPOSITION AND MARKET GROWTH

Some analysts have paid particular attention to the effects of product market composition and market scale. It is possible to test these additional hypotheses also.

One common theory in both the popular and the analytic literature is that of "deindustrialization."⁶⁹ This theory suggests that at least some of the slowdown in productivity growth since the 1960s has resulted from the shift in output, away from manufacturing and other goods-producing sectors in which productivity levels and rates of growth have

69. See, for example, Barry Bluestone and Bennett Harrison, *The Deindustrialization of America* (Basic Books, 1982); Lester C. Thurow, "The Productivity Problem" (Massachusetts Institute of Technology, Department of Economics, November 1980); and Gregory B. Christainsen and Robert H. Haveman, "The Determinants of the Decline in Measured Productivity Growth: An Evaluation," in Joint Economic Committee, *Productivity: The Foundation of Growth*, Special Study on Economic Change, vol. 10, 96 Cong. 2 sess. (GPO, 1980), pp. 1-17. We note that Bluestone and Harrison, despite their title, focus more on changing investment policies and what they call the "hypermobility of capital" than the direct effects of shifts in employment or output out of manufacturing.

historically been relatively high and technical change is likely to have its biggest impact, into service sectors in which productivity levels and growth rates have been relatively low.

If the deindustrialization hypothesis is correct, we should expect that aggregate productivity growth would vary directly with the rate of change in L_m , defined as the portion of total nonfarm private employment in the (one-digit) manufacturing sector.⁷⁰

Equations 8-1 and 8-2 of table 8 report the results of this test. Equation 8-1 shows that the manufacturing-share variable is significant when added to the technical model but has the wrong sign. When it is added to the more complete social model, it still has the wrong sign but is statistically insignificant. We conclude that this measure of sectoral composition does not help account for variations in productivity growth and should not be carried forward for further analysis.⁷¹

A complementary variant on the sectoral composition theme has emerged from recent Marxian discussions of the process of accumulation. Some Marxists define certain sectors as nonproductive because their workers do not create value, in the Marxian value-theoretic sense, but simply serve the functions of distributing commodities or realizing surplus value. If there were a significant shift of employment into these nonproductive sectors, according to this hypothesis, one might reasonably expect a retardation in the rate of growth of aggregate productivity. We can test this hypothesis in the same way as we have already explored the deindustrialization hypothesis. We define L_n as the portion of total nonfarm private employment in the one-digit sectors of trade and finance, insurance, and real estate. Adding this variable to the respective models,

70. This variable could alternatively have been defined in terms of the proportion of employment in the goods-producing sector, but we chose manufacturing for a more liberal test of the effects of sectoral shifts because the growth of productivity held up longer in manufacturing—through 1973—than in any other major sector.

For an additional review of the effects of changes in sectoral composition, see Martin Neil Baily, "The Productivity Growth Slowdown by Industry," *BPEA*, 2:1982, pp. 423–54.

71. The reason it has the wrong sign and is so significant in the technical model appears to reflect the fact that the manufacturing share increased during 1966–73 while productivity growth declined; because the technical model cannot account for the productivity decline during that period, it appears statistically in 8-1 that a rising manufacturing share is associated with slower productivity growth, a result that disappears once our social variables are added to the analysis.

Table 8. Sectoral Composition and Market Growth, 1948–79^a

<i>Independent variable</i>	<i>8-1</i>	<i>8-2</i>	<i>8-3</i>	<i>8-4</i>	<i>8-5</i>	<i>8-6</i>
λ^*	0.019 (6.25)	0.016 (7.46)	0.030 (5.23)	0.019 (4.54)	0.025 (3.46)	0.017 (4.46)
Δg	0.165 (4.38)	0.136 (3.28)	0.118 (2.72)	0.122 (4.37)	0.062 (1.30)	0.120 (4.27)
k_u	0.404 (3.44)	0.414 (4.70)	0.426 (2.89)	0.395 (4.36)	0.812 (5.35)	0.442 (4.77)
j	...	0.023 (2.24)	...	0.024 (3.49)	...	0.027 (4.01)
$\Delta w!$	...	0.058 (1.26)	...	0.075 (1.66)	...	0.068 (1.49)
z	...	-0.083 (-3.52)	...	-0.075 (-2.28)	...	-0.083 (-3.49)
p_f or p_x	-0.072 (-3.19)	-0.037 (-1.84)	-0.034 (-1.26)	-0.040 (-2.01)	-0.037 (-1.16)	-0.037 (-1.75)
C^*	...	0.010 (2.63)	...	0.009 (2.35)	...	0.011 (2.64)
l_m	-0.217 (-6.51)	-0.027 (-0.54)	...	...	...	...
l_n	...	...	-0.553 (-4.46)	-0.109 (-0.93)	...	...
y_{tr}	...	...	...	...	-0.418 (-2.62)	-0.040 (-0.40)
Summary statistic						
$\bar{R}^2$	0.797	0.896	0.843	0.898	0.577	0.895
Standard error of estimate	0.007	0.005	0.006	0.005	0.009	0.005
Durbin-Watson	1.903	2.179	1.976	2.270	1.663	2.275

Source: Authors' estimates based on data cited in the appendix.

a. The dependent variable is the decyclical rate of change of hourly output, q^* . The variable l_m is the rate of change in the manufacturing share of unemployment; l_n , the rate of change in the nonproduction sector's share of unemployment; and y_{tr} , the trend rate of change in real manufacturing output. Given first differences, actual years of observation are 1949–79. The numbers in parentheses are t -statistics. The input-price variable is entered as p_f in the technical model and p_x in the social model.

we would expect its coefficient to have a negative sign if the nonproductive-sector hypothesis is valid.⁷²

Equations 8-3 and 8-4 report the results of this test. As was shown for the manufacturing variable, this composition measure is significant

72. For a discussion of this possible effect, see Anwar Shaikh, "Towards a Critique of Keynesian Theory on the Role of the State" (New School for Social Research, Department of Economics, September 1980). To refer to these sectors as nonproductive sectors does not imply, of course, that the efficiency of production in those sectors—that is, value of the output per labor hour purchased—is irrelevant or constant through time. Growth of output per hour in these sectors also declined after 1966.

when added to the technical model but insignificant when added to the more complete social model. (In this case, at least, the variable has the right sign.) We choose not to carry forward this variable.

A third hypothesis about sectoral composition and market scale has been more widely discussed in the British and European literature than it has in the United States. This hypothesis is most commonly labeled Verdoorn's law or Kaldor's law. Although originally and typically applied to cross-sectional comparisons of productivity growth within manufacturing, the Verdoorn hypothesis may be at least provisionally and inferentially applied to variations in productivity growth over time.⁷³

According to the implicit logic of this hypothesis, rapid growth in market scale, resulting in rapid growth in marketed output, is likely to result in rapid growth in productivity for either (or both) of two important reasons. First, particularly in earlier stages of the development of domestic markets, rapid growth in effective demand is likely to make possible important economies of scale in the organization and production of industrial output. (The literature focuses primarily on industrial output because that sector is thought to correspond most closely to traditional hypotheses of Adam Smith about the efficiency effects of a finer technical division of labor.) Second, even at later stages of development, rapid and sustained growth in output is likely to permit and encourage large-scale and long-period innovations in the technique and organization of industrial production, at least in part as a result of declining worker resistance to technological change. Once these increases in productivity growth are realized, of course, they are likely to result in further expansions in the scale of output within a particular economy through further extension of the scale of the domestic market, through expansions of exports as a result of increasing international competitiveness, or through both. This anticipation of positive feedback on the scale of

73. There is a scattered literature on "Verdoorn's law." For a sampling, see the seminal piece by Nicholas Kaldor, originally written in 1966, "Causes of the Slow Rate of Economic Growth in the United Kingdom," in Kaldor, *Further Essays on Economic Theory* (Holmes and Meier, 1978), pp. 100–38; John Cornwall, "Diffusion, Convergence, and Kaldor's Laws," *Economic Journal*, vol. 86 (June 1976), pp. 307–14; A. Parikh, "Differences in Growth Rates and Kaldor's Laws," *Economica*, vol. 45 (February 1978), pp. 83–91; R. E. Rowthorn, "A Note on Verdoorn's Law," *Economic Journal*, vol. 89 (March 1979), pp. 131–33; and Robert Boyer and Pascal Petit, "Employment and Productivity in the EEC," *Cambridge Journal of Economics*, vol. 5 (March 1981), pp. 47–58.

output leads to models of “cumulative causation” in the Verdoorn literature. The policy implication is clear: “The central growth problem in a capitalist economy,” Michael J. Piore concludes, “becomes that of how to organize demand so that the required expansion is assured.”⁷⁴

One simple test of the Verdoorn hypothesis is possible and consistent at least with the spirit of the available literature: productivity growth over time should depend, other things being equal, on past long-term trends in industrial output. The more rapid the cumulative expansion of industrial output in the recent past—and therefore the more rapid the recent expansion of market scale—the more rapid will be the current increases in labor productivity. We follow the applied Verdoorn literature in defining a variable to test this hypothesis, tracing the growth of industrial output over a ten-year time horizon, and capturing its cumulative effects through a ten-year end-of-period moving average.⁷⁵ We thus define

$$y_{tr} = [(\sum_s y_{m_{t-s}})/10],$$

where s is 0, . . . , 9, and y_m is the annual rate of growth of real industrial output.

Equations 8-5 and 8-6 report these results. Again, as was shown for the manufacturing variable, and probably for the same reasons, the variable is statistically significant but with the wrong sign when added to the technical model. It is statistically insignificant if added to the social model.⁷⁶

CAPITAL SERVICES

We noted in our original discussion of capital intensity that the productivity of the utilized capital stock will depend on the degree of

74. Michael J. Piore, “The Theory of Macro-Economic Regulation and the Current Economic Crisis in the United States,” Working Paper 285 (MIT, Department of Economics, July 1981), p. 20.

75. The formulation of the ten-year moving average follows the example of Vladimir Brailovsky, “Industrialization and Oil in Mexico: A Long-Term Perspective” (Ministry of Industrial and Natural Resources, Mexico, September 1980). We are grateful to John Eatwell and Tom Michl for useful conversations about the time-series applications of the Verdoorn’s law analysis.

76. The fact that the trend-output variable is not significant does not fully vitiate the trend-growth analysis. We note that our own analysis of the Schumpeter effect is somewhat

nonobsolescence of the available capital stock. We introduce here some alternative tests for this effect.

One is to equate obsolescence with the age of the capital stock, postulating that a relatively older capital stock, other things being equal, will provide relatively fewer productive capital services. (This would presume a lag in the adaptation of the market valuation of capital goods.)⁷⁷

A second, more complicated test follows an idea proposed by Martin Neil Baily.⁷⁸ He argues that the relative efficiency of the current available capital stock will depend substantially on the extent of past unanticipated price changes in the relative price of inputs complementary to capital services, and particularly in the relative price of energy inputs. If complementary input prices remain predictable, conforming to expectations at the time of the original purchase of the capital stock, then a relatively large fraction of the current available capital stock will remain nonobsolescent. If, in contrast, there has been a sharp upturn in relative energy costs since the original purchases of the current capital stock, Baily concludes, "energy-inefficient vintages of capital will be utilized less intensively and scrapped earlier following a rise in energy prices."⁷⁹ We looked at two alternative versions of this hypothesis, and the results are reported in the note below.⁸⁰

We can explore the hypothesis through one further test. Particularly as highlighted by Baily, energy-price shocks are viewed as reducing the

analogous; ours has the advantage, we think, of focusing more directly on factors related to innovation and avoiding confusion between the rate of growth of the economy itself, on the one hand, and changes in the pace of innovation or the technical division of labor.

77. For this version we directly measured the relative age of the capital stock, K_a , as the average age of industrial equipment expressed as a deviation around its mean for the period of observation from 1948 to 1979. When this variable, expressed as a rate of change, is added to equation 3-2, it has the expected sign and is statistically significant. When it is added to the social model, it becomes insignificant.

78. See Baily, "Productivity and the Services of Capital and Labor."

79. *Ibid.*, p. 20.

80. We begin with the proposition that the utilized, nonobsolescent capital stock may be defined as $K^* = gnK$, where g , as above, is the rate of capacity utilization; n is an index of the nonobsolescence of capital, with $0 \leq n \leq 1$, measured in units that reflect the relative obsolescence of the utilized capital stock; and, as before, K is the measured real available capital stock.

We then propose that n be a function of unanticipated price variability in the relative price of external inputs, $n = (1 - p_u)^\pi$, with $\pi > 0$, where p_u is a measure of unanticipated price changes in the relative price of nature-based inputs which are complementary to capital services, and π is an adjustment coefficient. We further propose that this expression

relative efficiency of utilized capital inputs after the initial oil-price shocks hit in 1973 (with potentially comparable effects after the second wave of increases in 1979). Interpreted quite literally, this suggests that the positive effects of increases in the capital-labor ratio were dampened after 1973. This supposition is tested through a piece-wise regression in which the slope of the coefficient on the utilized capital-labor ratio is allowed to vary after 1973.⁸¹

None of these tests, whose details are reported in notes, provides support for the hypothesis about variations in the nonobsolescence of the capital stock. While we continue to think that the hypothesis is plausible on theoretical grounds, we are unable to find evidence to support it.⁸²

for p_u can be formulated in either of two ways. One is

$$p_u = \left| \left(\frac{p_x|_{t-a} / p_{x_{t-a}}}{a} \right) - \left(\frac{p_x|_{t-a-m} / p_{x_{t-a-m}}}{m} \right) \right|,$$

where a is the average age of the current stock of fixed capital; m is the period over which price expectations are formed; and the absolute value of the difference between the two price terms in the expression embodies the hypothesis that unanticipated price changes in *either* direction would reduce the nonobsolescence of the utilized capital stock.

The same variable can be formulated without the expression for the absolute value, indicating that unanticipated price increases will increase the obsolescence of the utilized capital stock while unanticipated price decreases will have the opposite effect.

Neither formulation was statistically significant, and the latter version actually had the wrong sign. We also tested a version of this variable in which p_f was substituted for p_x in the definition of p_u . This variable had even less statistical effect.

81. Use of piece-wise regression ensures that we test for a change in the slope of the coefficient on the capital intensity variable and not simply for a change in the intercept of the equation, as we did with the dummy variables in table 3, and that we constrain the coefficients on the effects of capital intensity to be equal at $t = 1973$ and to allow them to differ thereafter.

Adding this variable to both models results in a coefficient with the wrong sign; whatever the meaning, it is difficult to sustain the empirical conclusion that unanticipated external variability in input prices, other things being equal, either dampened the contribution of rising capital intensity or slowed the rate of productivity growth.

82. We note here that we tested one other hypothesis concerning price effects and the productivity slowdown. Michael R. Darby has proposed that the Nixon round of price controls artificially (and temporarily) dampened prices and therefore artificially overstated the value of real output (with respect to trend), thereby generating artificially high estimates of productivity growth in 1972 and 1973. He tests this hypothesis with a vector of dummy variables linearly increasing from 1971:2 to 1973:1 and then linearly decreasing back to zero in 1974:4. We cannot perfectly reproduce his tests because we are constrained to work with annual data. But we sought an approximation by defining a dummy variable

FINAL ESTIMATION

These sequential tests provide only one additional variable for inclusion in a final round of estimations. Based on earlier results, and particularly on the effects of adding variables to the social model, it would appear that only the measure of educational attainment described above deserves further consideration. This suggests that we might treat the results reported in column 7-2 as the most complete possible operational version of the general social model.

The particular form of this final specification seems to us relatively less important than the full effect of all the additional tests reported in this section. We have tested as many additional hypotheses as we could identify in the literature. The results seem consistent. Many variables, when included in the simple technical model first reported in 3-2, appear to be significant. When added to the more inclusive social model, only one effect—that of educational attainment—holds up. At the same time, the basic results of the social model itself remain robust and consistent throughout.

This strengthens the premise with which we began: the recent literature has not only been unable to explain much of the productivity slowdown but has also been misled by the underspecification of the basic technical model on which it has built its analyses. The social model developed here can both provide what appear to be the missing clues in the mystery of declining productivity growth and correct some of the misperceptions and biases that have resulted from this underspecification.

In particular, there appear to be four important instances of underspecification bias in the estimations reported in these various comparative exercises: they involve v , the variable measuring changes in educational attainment; l_f , the proxy for changes in the sex composition of

that assumes the values of 0.5 in 1972, 1.0 in 1973, and 0.5 in 1974. One would, according to Darby's hypothesis, expect a positive sign for this proxy.

When this variable is added to the technical model, the variable is statistically significant but has the wrong sign. When it is added to the social model, it has the correct sign but is statistically insignificant, with a t -statistic of only 0.77. We cannot fully explain the inconsistency with Darby's results, given our annual data, but we suspect that his results suffer from bias as a result of exclusion of our social variables. See Michael R. Darby, "The U.S. Productivity Slowdown: A Case of Statistical Myopia," Working Paper 1018 (National Bureau of Economic Research, November 1982).

the labor force; the coefficients on g , the rate of change of capacity utilization; and k_u , the rate of change of the utilized capital-labor ratio. The first two examples of underspecification bias reinforce prevalent conceptions about the productivity effects of changes in the composition of the labor force, and thus strengthen tendencies to blame the unskilled and women for the underlying sources of stagnation. The second two examples reflect the anti-Keynesian strands of thought in recent discussions of macroeconomics: if the coefficients on g and Δg are relatively low (as in 3-2) and the coefficients on k_u are relatively high (also true in 3-2), these findings reinforce the beliefs of current policymakers, who tend to rely heavily on efforts to increase the rate of investment directly through profit subsidies rather than through efforts to expand the growth of effective demand. In either case, judging by the results of our social model, the potential harvest of policies grounded in this technical model will be dramatically overestimated.

Policy Implications

We have identified some social factors affecting aggregate productivity that help illuminate the decline in productivity growth in the United States. In particular, we have concentrated on the effects of declining work intensity and lagging business innovation. Attention to these social determinants appears to provide some crucial missing clues to the productivity puzzle.

Does this offer any guidelines for policies to help revive productivity growth? We limit ourselves to two general observations.

The first is that it is possible to address problems of work intensity and business innovation through direct policy intervention. The second is that the analysis presented in this paper does not and cannot distinguish among the variety of possible policy approaches to these social sources of the productivity slowdown. Although this analysis helps to underscore the importance of the problems, it is incapable of ranking various alternatives on the basis of either efficacy or political desirability.

Consider a few leading alternatives: conservatives propose to restore work intensity through intensified labor market discipline (and, we might add, assaults on unions) and to revive business innovation by unleashing private enterprise from the collar of government regulation. Neo-liberals

propose to restore work intensity through a new tripartite social contract among business, labor, and the government and suggest planning instruments like those of the Japanese to foster longer-term business planning and innovation. Progressives and leftists propose to raise work intensity by increasing worker motivation through more participatory and democratic organization of the workplace and by rapid wage growth; they suggest a combination of full-employment programs, democratic planning, and rising minimum wages to spur greater business innovation. If necessary they recommend supplementing these instruments with public innovation and investment.⁸³

Choices among these alternative approaches involve clear conflicts in basic policy directions and therefore involve fundamental political questions about economic priorities. Although this analysis of the social determinants of the productivity slowdown helps dramatize the importance of this kind of political economic debate, it is incapable of resolving it. One must return to more basic considerations of political and economic possibility and desirability to move from analysis to policy. If the productivity slowdown is no longer so puzzling, policies to address that slowdown can at last be debated with the clarity and coherence they deserve.

APPENDIX

Variables and Data Sources

LISTED BELOW are the variables entering our empirical analysis and, where relevant, the methods used to compile the time series. Except where otherwise noted, the data apply to the nonfarm private business sector of the U.S. economy. The source notes do not provide sufficient detail on every data adjustment or calculation based on the cited sources; interested readers should contact the authors for further clarification.⁸⁴

C = Business-failure rate, from *Economic Report of the President, January 1981*, table B-91.

83. We discuss the differences among these policy approaches in detail in parts 2 and 3 of Bowles, Gordon, and Weisskopf, *Beyond the Waste Land*.

84. The only variables not listed here are E , D , and R , which are derived from variables reported here by text equations 1 and 7, respectively.

- G = Ratio of actual to potential output, based on series provided by Bureau of Economic Analysis, as updated in *Survey of Current Business*, vol. 62 (April 1982), p. 25.
- J = Cost of job loss, calculated as reported in the text, supplied by Juliet B. Schor and Samuel Bowles. Sources reported in their paper, "Conflict in the Employment Relation and Cost of Job Loss," Working Paper 6 (Economics Institute of the Center for Democratic Alternatives, 1983).
- K = Real capital stock, defined as the weighted sum of the net ($\frac{1}{4}$) and gross ($\frac{3}{4}$) values; mid-year estimates were obtained by averaging previous and current end-year values, based on U.S. Department of Commerce, Bureau of Economic Analysis, *Fixed Reproducible Tangible Wealth in the United States, 1925-79* (Government Printing Office, March 1982).
- K_a = Age of capital stock, based on series for gross stocks of equipment in industry, from U.S. Bureau of the Census, *Historical Statistics of the United States* (GPO, 1976), Series F-517, and Bureau of the Census, *Statistical Abstract of the United States*.
- L = Basic BLS index of hours of all persons, as reported in *Economic Report of the President, January 1981*, table B-38.
- L_f = Percentage of labor force that is female, from U.S. Department of Labor, *Employment and Training Report of the President, 1981* (GPO, 1981), table A-2.
- L_m = Percentage of nonagricultural employment in manufacturing, from *Employment and Training Report of the President, 1981*, table C-1.
- L_n = Percentage of nonagricultural employment in trade and in finance, insurance, and real estate, from *Employment and Training Report of the President, 1981*, table C-1.
- L_y = Percentage of the labor force between ages sixteen and twenty-four, from *Employment and Training Report of the President, 1981*, table A-5.
- P_f = Calculated by the same procedure as that for determining P_x , with BLS index for fuels in the numerator.
- P_x = Calculated by dividing the BLS quarterly price index for nonagricultural crude materials by the corresponding implicit price deflator for gross domestic product, based on data from

the national income and product accounts, updated in *Survey of Current Business*, vol. 62 (July 1982).

Q = Index of production-worker hourly output, $(Y/L) \cdot (1 + S)$.

S = Ratio of nonproduction workers to production workers in private nonagricultural establishments, based on U.S. Bureau of Labor Statistics, *Employment and Earnings, United States, 1909–78* (GPO, 1979), updated in *Employment and Earnings*, June 1982, pp. 2–3.

U = Percent of nonagricultural labor force that is unionized, based on Bureau of Labor Statistics, *Directory of National Unions and Employee Associations, 1979*, Bulletin 2079 (GPO, September 1980), incorporating revisions reported in BLS, “Corrected Data on Labor Organization Membership—1980,” USDL Release 81-446, September 18, 1981.

V = Median years of educational attainment of the civilian labor force, from *Historical Statistics of the United States*, table 13, with linear interpolations for earlier years.

$W!$ = Based on new series reported in Thomas E. Weisskopf, “A New Spendable Earnings Series,” Technical Note 2 (Economics Institute of the Center for Democratic Alternatives, 1983).

X = Energy consumed by industry, measured in Btu units, based on *Statistical Abstract of the United States* (various years).

Y = Basic Bureau of Labor Statistics index of output, as reported in *Economic Report of the President, January 1981*, table B-38.

Y_{ir} = Based on index of industrial output, from *Economic Report of the President, January 1981*, table B-40.

Z = Based on splicing of BLS data for manufacturing on frequency of work-time lost from industrial accidents, periods before and after 1970. For method and sources, see Michele I. Naples and David M. Gordon, “The Industrial Accident Rate: Creating a Consistent Time Series,” Technical Note 1 (Economics Institute of the Center for Democratic Alternatives, 1981).