

Factor Utilization and Margins for Adjusting Output: Evidence from Manufacturing Plants

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This paper describes patterns of factor utilization and output adjustment at the plant level for a wide range of manufacturing industries. We explain why manufacturing plants may differ quite a bit in how they accomplish output adjustments, depending on shutdown cost aspects of technology. Assembly-type operations with low shutdown costs would primarily vary the work period of the plant, whereas continuous processing plants with large shutdown costs would adjust instantaneous flow rates of production. For larger output increases, a lengthening of the work period by assemblers would entail employment changes, whereas continuous processors would be more apt to relax physical capital constraints. We use micro survey data on the organization of actual and capacity plant operations to describe the observed patterns of adjustment in individual manufacturing industries and find substantial heterogeneity across industries. For manufacturing as a whole, the work week appears to be a significant margin of adjustment.

Recent literature suggests that the relationships between marginal costs and output levels of manufacturers are complicated by the presence of multiple ways to achieve output changes and of one-time costs to adjusting some factors of production. The shape of marginal costs depends on which factors of production are adjusted, and different factors should be adjusted in differing circumstances, depending on whether it is desirable to incur the one-time adjustment costs. Such a view implies that marginal costs may be downward-sloping in some relevant ranges of output fluctuations and upward-sloping in other relevant ranges, with substantial discontinuities at the points where different patterns of factor adjustment come into play.

If such non-convexities in marginal cost curves are commonplace, this fact should be incorporated in economic models of price determination, which generally assume that prices are set at marginal cost. Furthermore, the recent arguments for the existence of non-convexities in marginal costs generally emphasize interactions between costs and how manufacturing plant work periods are configured in terms of such features as the number of operating shifts and days of operation. A related literature also emphasizes the need to account for changes in the workperiod of capital in studying the cyclical productivity growth (Beaulieu and Matthey (1995), Burnside, Eichenbaum, and Rebello (1995), Shapiro (1996), among others). Here, we introduce a way of thinking about these issues which allows for large differences across plants and industries in the extent of fixity of various factors of production and corresponding heterogeneity in patterns of factor adjustment. In particular, we posit that the technologies of individual manufacturing plants could range from “pure assembly” type operations, where shutdown and startup costs are low and all output adjustments are accomplished through varying the plants’ work periods, to “pure continuous processing” type operations, where shutdown and startup costs are large and none of the output adjustments are accomplished through varying the plants’ within-week work periods.

We investigate the empirical relevance of these issues by studying patterns of factor utilization reported in the Census Bureau’s Survey of Plant Capacity (SPC). The evidence from the SPC turns out to be consistent with the presence of this broad range of technology types, but we find that, on average in all of manufacturing, the use of the plant

work period margin is relatively common, so the “pure assembly” type characterization is closer to the truth in the aggregate.

Our results also suggest that measuring changes over time in the work period of capital in various manufacturing industries is important to understanding productivity growth. Many economists have puzzled over why estimates of total factor productivity growth tend to be very procyclical. Although shifts in aggregate demand are thought by many to be the prevailing source of business cycle fluctuations, estimates often show that total factor productivity growth picks up when output is expanding, and productivity growth slows in contractions, as if exogenous technological fluctuations were driving the fluctuations in output. A sizable literature on capital utilization—surveyed by Beaulieu and Matthey (1995) and extended further by Shapiro (1996)—emphasizes that the appearance of strongly procyclical productivity could be due to the mismeasurement of changes in capital service flows. Some recent studies of actual plant-level behavior have confirmed the importance of the work period of capital margin of output adjustment, particularly for assembly type operations (Aizcorbe 1994, Bresnahan and Ramey 1994). However, other industry studies have emphasized variation in the momentary flow rates of production at continuous processing operations (e.g., Bertin, Bresnahan, and Raff 1996), which are not dependent on changes in the work period. We review the evidence for all manufacturing industries and describe the extent to which the duration of capital use can or cannot be taken as fixed.

I. COSTS AND ADJUSTMENT MARGINS

Production Volume, Flow, and Costs

Assume for now that there are two short-run fixed factors of production, the stocks of capital (K) and labor (N). However, the flows of services from these stocks are not fixed. Plant managers decide each quarter (t) how intensively to use the stocks in each moment (m) of the quarter.

The relationships between service flows and stocks depend both on the duration of use of the factors—how long they are employed during the period—and on the intensity of use at each moment when the factors are employed. For labor, we assume that the intensity of use at a moment (m) can be indexed by the number of employees actually at work in that plant (j), which we denote $L_{jt}(m)$. The capital stock might or might not be divisible in this sense of being able to operate some units and not others. Given that we cannot separately observe usage of components of the capital stock, we will focus on whether or not any part of the plant is operating; the indicator variable, $\mathbb{1}_{jt}(m)$, equals

1 if the plant is open at moment m and equals 0 otherwise. When capital is operating, we define the aggregate intensity with which the plant’s capital stock is worked at moment m , its “speed” $s_{jt}(m)$, to be the ratio of the flow of services from the capital stock, $K_{jt}^s(m)$, to the level of the capital stock, $K_{jt}(m)$. The “speed” of the aggregate plant capital stock can be varied either by using each piece of capital at a higher operating rate or by increasing the number of pieces of capital operating. Putting this notation together, the capital service flow at moment m is given by

$$(1) \quad K_{jt}^s(m) = \mathbb{1}_{jt}(m)s_{jt}(m)K_{jt}(m).$$

In addition to the primary factors of production, labor and capital, manufacturing plants also use intermediate inputs, such as raw materials, components manufactured by others, electricity, and purchased business services. For generality, we assume that the plant’s instantaneous production function, $f_{jt}(\cdot)$, also depends on the flow rate of these materials and other intermediates, $R_{jt}(m)$. Letting discrete time (t) be a quarterly interval between moments m_{t-1} and m_t , note that the volume of production over the quarter Q is the sum (integral) of instantaneous output:

$$(2) \quad Q_{jt} = \int_{m_{t-1}}^{m_t} f_{jt}(L_{jt}(m), K_{jt}^s(m), R_{jt}(m); K_{jt}, N_{jt}) dm.$$

Furthermore, because momentary output is non-zero only if the plant is open ($\mathbb{1}_{jt}(m) = 1$), the volume of output also can be written as:

$$(3) \quad Q_{jt} = \int_{m_{t-1}}^{m_t} \mathbb{1}_{jt}(m) f_{jt}(L_{jt}(m), K_{jt}^s(m), R_{jt}(m); K_{jt}, N_{jt}) dm.$$

Alchian (1959) is among those who early on emphasized the distinction between flow rates of production f and volumes of production Q for understanding production costs. The key insight is that in some production situations the flow rate of production can be altered easily, and in other situations large costs are incurred if the flow differs much from a norm. If shutdown and startup costs are small enough, intermittent production will be optimal for those producers with relatively fixed flow rates. The cost-minimization decision problem of the firm can separate into the twofold choice of how long to leave the plant open during the period, a decision about $\mathbb{1}_{jt}(m)$, and how intensively to operate any time the plant is open, a decision about f_{jt} (Maloney and McCormick 1983). On the other hand, if shutdown or startup costs are large enough, the plant will be operated continuously, and all of the variation in output will come from changes in the instantaneous flow rate of production, f_{jt} .

The decisions about the duration of operations are complicated by the fact that there is much discreteness in the labor input of individual members of the workforce. Employees are scheduled to work for particular portions of

days (shifts) and generally have days or weeks away from the job. Plant operation schedules generally reflect similar calendar effects. For the quarterly intervals we consider here, the overall workperiod of the plant

$$H_{jt}^K = \int_{m_{t-1}}^{m_t} f_{jt}(m) dm$$

can be decomposed into the product of four observables, weeks-per-quarter (*WEEKS*), days-per-week (*DAYS*), shifts-per-day (*SHIFTS*), and shift-length in hours-per-shift (*LENGTH*):

$$(4) \quad H_{jt}^K = WEEKS_{jt} DAYS_{jt} SHIFTS_{jt} LENGTH_{jt}.$$

Plant managers can alter the plant work period by changing any of these duration variables.

Costs and Hierarchies of Adjustment Margins

For understanding price determination, it is useful to understand marginal costs. In a static model, the marginal cost schedule of a plant indicates how overall costs depend on incremental changes in output, assuming that factors of production are adjusted in a way which minimize the cost of achieving the given output level. Dynamic models also can recognize that speeds of adjustment affect costs. In general, different margins for adjusting output have different static marginal costs and different adjustment costs. We formalize this idea by writing out the following total cost function:

$$(5) \quad C_{jt}(Q_{jt}(m)) = F_{jt}(L_{jt}(m), K_{jt}^s(m), R_{jt}(m), Z_{jt}(m)) \\ + L I(L) + K^s I(K^s) \\ + R I(R) + \sum_{k=1}^{n_z} Z_k I(Z_k).$$

Here, the overall instantaneous costs $C_{jt}(Q_{jt}(m))$ depend on a static piece, F_{jt} , that reflects, for example, that if output is adjusted by increasing labor input L_{jt} , then the overall wage bill of the plant will rise. Similarly, variable costs depend on the instantaneous rate of materials usage $R_{jt}(m)$ and possibly also on the pace of capital service flows K_{jt}^s through such channels as endogenous depreciation. Implicitly, the static costs are dependent on factor prices, including the possible kink in the wage schedule at the point where the firm begins to pay overtime premia. For expository purposes, we have represented in a vector Z all production choice variables other than labor, capital services, and materials; for example, Z includes the state variables describing the configuration of the plant work period in terms of the number of weeks, days, shifts, and shift length. The other terms

in the total cost function are adjustment costs; $I(\cdot)$ is an indicator variable for whether or not the input level of the given factor has changed.

In a world with no uncertainty and decisions that pertain to only one period, the marginal cost function for a manufacturing plant could be readily derived from this total cost function by deriving its “slope” with respect to output. In problems with non-convexities such as those considered here, this essentially is done by calculating how the optimal factor input levels would change as output varies and by evaluating the changes in the cost function between optimally perturbed factor input levels. Multiperiod decisionmaking and uncertainty add realism to the problem but also create the need for more fully specifying a dynamic, stochastic programming problem.

Some of the basic insights of such a formalization have been well described by Bresnahan and Ramey (1994). For example, if the plant would find it optimal to adjust output by changing aspects of the work period which affect the degree of overtime use, then the marginal cost function is unlikely to be smoothly upward sloping as output increases. When overtime premia trigger at 40 hours per week, an expansion of output along the shift length component of the plant work period margin H_{jt}^K encounters a discontinuity in marginal costs at this threshold, assuming a fixed stock of workers (N_{jt}) and a fixed number of workers per operating shift. However, this particular expansion path is not necessarily optimal; plant managers can avoid the use of overtime by hiring additional workers, say by adding an additional shift. At the overtime threshold, the increased static marginal costs can be avoided if the shift margin (represented in Z) is used to spread the additional labor hours over a larger number of shifts. However, in this event the hiring adjustment costs must be absorbed. As Bresnahan and Ramey (1994) point out, overtime hours are more likely to be used than shift changes if the output adjustments are small or temporary, whereas large, permanent output adjustments are more likely to result in shift changes.

These complications have important implications for the relationship between output changes and incremental costs. For example, a plant already using a lot of overtime and considering expanding output further by adding an additional shift faces a kink in the marginal cost schedule where the switch to an extra shift occurs. Conditional on a shift change, the overtime premia are eliminated, lowering marginal costs. Furthermore, given an additional shift, the plant may initially enter a region of increasing returns to scale (greater efficiency as output increases) because the productivity of the group work effort may be greatly inhibited by understaffing of the additional shift. This characteristic of labor productivity, that labor must be added in increments of fully staffed shifts, is most characteristic

of assembly line operations. Assembly line operations may face increasing marginal costs over some ranges of output variation and declining marginal costs over other ranges of output variation.

Extremes of Technology Types

For illustrative purposes, we discuss two technology types at the opposite extremes in the nature of the adjustment costs and the degree of lumpiness in labor productivity. We will call “pure assemblers” those manufacturing operations which face very low within-day shutdown and startup costs. Pure assemblers also face very large costs of adjusting flow rates of materials or the speed of capital input and exhibit a high degree of lumpiness in labor productivity (i.e., the need for fully staffed shifts). In contrast, “pure continuous processors” face very large shutdown and startup costs and do not use the work period margin except for infrequent, critical maintenance or under very adverse demand conditions, when the plant will be shut down for weeks at a time. Adjustment costs for flow rates of production are low for continuous processors. Furthermore, we assume that beyond some small amount of overhead labor, the labor productivity of individual workers at continuous processors is not highly dependent on the exact number of workers at the plant at that time; in the extreme, pure continuous processors are very capital and materials intensive, and the marginal product of labor is zero above the overhead threshold.

The assumed characteristics of the cost function for pure assemblers imply that the work period margin is the only operative margin of adjustment for such plants. Accordingly, with cost-minimizing factor inputs, the volume production function of pure assemblers can be represented in a simplified form which illustrates that instantaneous production does not vary across moments when the plant is open,

$$(6) \quad Q_{jt} = \int_{m_{t-1}}^{m_t} f_{jt}(m) \overline{f_{jt}} dm = \overline{f_{jt}} \int_{m_{t-1}}^{m_t} f_{jt}(m) dm.$$

In other words, the volume of output is proportional to the plant work period:

$$(7) \quad Q_{jt} = \overline{f_{jt}} H_{jt}^K.$$

For pure continuous processors, the large shutdown and startup costs make the plant bunch the shutdown times into continuous intervals. For example, if some shutdown time is needed to conduct necessary maintenance that temporarily interrupts production, the plant is likely to try to complete all such needed maintenance in a single downtime. Within-week downtime would not be regularly observed,

but the plant might shut down for one or more contiguous weeks each quarter to conduct the maintenance.¹

At the cost-minimizing input levels, labor intensity would be fixed at the overhead amount L . If capital services are dependent only on the size of the capital stock and duration, not on “speed” effects, then only variation in the instantaneous flow of materials, R , would be important for explaining instantaneous output flows of pure continuous processors:

$$(8) \quad f_{jt}(m) = f_{jt}(R_{jt}(m); s_{jt}, L_{jt}, K_{jt}, N_{jt}).$$

As a first order approximation to this function, we represent the instantaneous output flow of pure continuous processors as proportional to the flow of materials:

$$(9) \quad f_{jt}(m) = R_{jt}(m) \overline{g_{jt}}.$$

Accordingly, the volume of production for a pure continuous processor can be written as

$$(10) \quad Q_{jt} = \int_{m_{t-1}}^{m_t} f_{jt}(m) R_{jt}(m) \overline{g_{jt}} dm = \overline{g_{jt}} \int_{m_{t-1}}^{m_t} f_{jt}(m) R_{jt}(m) dm.$$

Furthermore, the volume of production will be proportional to the plant work period:

$$(11) \quad Q_{jt} = R_{jt}^* \overline{g_{jt}} H_{jt}^k,$$

with the factor of proportionality depending on the average flow rate of materials R_{jt}^* when the plant is open during the quarter. Given our assumption that continuous processors vary quarterly work periods only in weekly increments, and the number of days per week, shifts per day, and hours per shift are fixed at a continuous operating configuration (24 hours per day for 7 days, or 168 hours per week), this implies

$$(12) \quad Q_{jt} = WEEKS_{jt} R_{jt}^* \overline{g_{jt}} 168.$$

II. EVIDENCE FROM THE SPC

Why Study the SPC Data?

To learn about the relative prevalence of these technology types, a direct estimate of the cost function (5), which really contains the parameters of interest, is preferable. However, developing empirical evidence on this matter is difficult both because the needed data on output levels, factor in-

1. In the face of very adverse demand conditions, shutdowns of continuous processors are likely to extend for periods that exceed a few weeks. The high shutdown and startup costs imply that when such control of finished goods inventory through downtime is exerted, this will be accomplished, insofar as possible, by extending the duration of maintenance shutdowns.

puts, and factor prices are not fully available, and because there are some important econometric issues which are difficult to address properly in such cost function estimation. For example, ordinary least squares estimation of the cost function parameters via equation (5) is unlikely to provide precise, consistent estimates: as time evolves, favorable shocks to technology or to factor prices can cause marginal costs to decline as output increases, even if diminishing short-run returns to scale are important in the absence of such shocks. Appropriate (relevant and exogenous) demand-side instruments are difficult to find.

We can overcome some of these difficulties by working with the data from the Census Survey of Plant Capacity (SPC). The SPC microdata report information on individual manufacturing plants' output and factor input levels, including the configuration of their work periods. Thus, for example, we can investigate whether the special forms of the volume production functions for either pure assemblers or continuous processors (equations (7) and (12)) fit the data well.

The SPC data also contain information on capacity (output) utilization and factor utilization relative to hypothetical levels of factor inputs at capacity. As we will explain in more detail below, the normalizations implicit in the construction of these utilization measures help us control for the effect of supply (technology) shocks, leading us to focus not just on how output and factor inputs have changed over time, but also on how much output and factor inputs differ from their configurations at capacity.

Information on Actual Operations

The SPC questionnaires were sent to a (probability based) subsample of the manufacturing plants which participated in the Census Bureau's Annual Survey of Manufactures (ASM). In terms of industry composition, representation is quite broad. We study the results of the surveys from the ten years between 1979 and 1988, a period when respondents were asked about the variables of interest. After the end of each year in this period, about 8,000 to 9,000 manufacturing establishments were asked to report on various characteristics of their actual and capacity fourth quarter operations in the preceding year. Some panel members failed to respond to all of the questions. We use only the 16,812 observations from those plants that fully responded to the questions of interest in each year they were a member of the sample. See Matthey and Strongin (1995) for a fuller description of when panel members were dropped for non-response and other data problems.

Respondents were asked about the work period of the plant, in actuality and at capacity, in terms of how many hours per day (*HOURS*), days per week (*DAYS*), and weeks

per quarter (*WEEKS*) the plant was or would be in operation. Thus, the work period of the plant, H_{jt}^K can be measured for the fourth quarter as a whole as the product of *HOURS*, *DAYS*, and *WEEKS*. Information on the number of shifts per day (*SHIFTS*) also was collected; we compute hours per shift (*LENGTH*) by dividing hours per day by the number of shifts per day.

Tabulations of the responses show that in manufacturing as a whole about 65 percent of the plants were open every week of the quarter (Table 1).² Another 25 percent of the plants shut down for only one week of the quarter. Shutdowns of manufacturing plants for more than one week per quarter were relatively rare. However, within-week shutdowns were relatively common. About 58 percent of the plants were open only five days per week. Another 12 percent of the plants shut down exactly one day per week. Within-day shutdowns also were relatively common. About 19 percent of the plants operated only one shift per day. Furthermore, among the 29 percent of the plants that operated two shifts per day, less than 13 percent lengthened these shifts to the 12-hour shift-length which would be needed to keep the plant open 24 hours per day. This simple descriptive evidence that within-week and within-day shutdowns were relatively common suggests that the large shutdown and startup costs which characterize the "pure continuous processor" technology type were not very pervasive in the manufacturing sector as a whole.

Further analysis, however, shows that the roughly 25 percent of plants that ran 24 hours per day, seven days per week were clustered in a relatively few industries. In other words, there was considerably more homogeneity of workweek practices within industries (defined in terms of four-digit SIC classifications) than of workweek practices within manufacturing as a whole.

To show this higher degree of homogeneity within industries, we have classified each four-digit SIC industry into industry groups on the basis of the characteristics of the (capacity or actual) work period of the SPC-reporting plants from that industry. As explained in more detail in Appendix 2 of Matthey and Strongin (1995), continuous processing industries were identified by computing the average work period at capacity, H^{Kc} , for each industry and calling "continuous processors" those industries which would extend operations to virtually every hour of the quarter at capacity. The remaining industries were split into roughly two groups, depending on whether the actual plant work periods in those industries had high coefficients of

2. In about 2 percent of the cases, plants report actual operations of 14 weeks, likely reflecting reference to accounting system calendars which consider this to be the number of weeks in some of the quarters.

TABLE 1
ORGANIZATION OF THE WORK PERIOD
IN MANUFACTURING
(PERCENT OF OBSERVATIONS IN GROUP)

	INDUSTRY GROUP			
	TOTAL MFG.	CONTINUOUS PROCESSING	VARIABLE WORK PERIOD	OTHER INDUSTRIES
WEEKS PER QUARTER (WEEKS)				
<8	0.3	0.4	0.3	0.1
8–11	9.4	4.8	13.7	7.4
12	25.1	11.4	36.2	21.3
13	63.1	81.0	48.2	69.0
>13	2.0	2.4	1.7	2.2
DAYS PER WEEK (DAYS)				
<5	2.0	0.4	2.6	2.5
5	57.9	11.0	78.4	68.3
6	12.0	4.9	14.5	14.4
7	28.0	83.6	4.5	14.8
SHIFTS PER DAY (SHIFTS)				
1	19.0	1.0	27.3	22.4
2	28.8	8.8	40.4	29.1
3	52.2	90.1	32.3	48.5
HOURS PER SHIFT (LENGTH)				
<8	6.3	1.3	9.1	6.8
8	80.7	91.3	74.9	79.8
>8	13.0	7.4	16.0	13.4
NUMBER OF OBSERVATIONS	16,812	4,311	7,215	5,286

SOURCE: Calculations by the authors from the Survey of Plant Capacity microdata.

NOTE: This frequency distribution pertains to observations from the 1979–1983 and 1984–1988 ASM waves.

variation over time. Those industries with plants with the highest variation in work periods are called “variable work period” industries. The resulting taxonomy is consistent with some of the stylized facts in the economics literature; for example, the blast furnace industry studied by Bertin, Bresnahan, and Raff (1996) is classified as a continuous

processing industry, and the auto assembler industry studied by Bresnahan and Ramey (1994) and others is classified as a variable work period industry. See Matthey and Strongin (1995) for a complete listing of this classification of four-digit SIC industries.

The final three columns of Table 1 show that there was considerably more homogeneity of work period practices within these industry groups than within total manufacturing. About 90 percent of the 4,311 plant observations in the continuous processing industries showed operations extending for three eight-hour shifts per day, and about 7 percent run around the clock by having two twelve-hour shifts. Among plants in continuous processing industries, within-week shutdowns also were rare but were somewhat more common than within-day shutdowns; although only about 3 percent shut down overnight during the main work-week, about 16 percent of the plants shut down for one or two days per week.

In contrast, more than 78 percent of the plants in the variable work period industries were open five days and shut down exactly two days per week. Within-day shutdowns also were more common in this group than for continuous processors; about two-thirds of the plants ran only one or two shifts per day, with most shifts being no more than eight hours. Only a small fraction of plants in this group operated 24 hours per day.

This simple descriptive evidence that within-week and within-day shutdowns were relatively uncommon in continuous processing industries suggests that the “pure continuous processor” type of cost and production function might be applicable to these industries.³

Similarly, the “pure assembler” type of cost and production function might be applicable in the variable work period industries. However, additional evidence is needed to discern whether the observed workweek behaviors of plants in these industry groups really do reflect technological differences or instead reflect differences in the demand profiles for the products of these industries.

One alternative possibility to a technological explanation for the observed workweek differences is that all industries face similarly low shutdown and startup adjustment costs, but those industries we have classified as continuous processors experienced stronger demand than other industries in this sample period. To be more precise, it is possible that plants in all industries had similar (less than

3. The fact that within-week and within-day shutdowns were relatively uncommon in continuous processing industries is not a tautological implication of the taxonomy which defined continuous processing industries; the continuous, non-continuous distinction was drawn on the basis of the characteristics of plants at capacity, not on the actual operating patterns of the plants.

continuous) target workweeks, but the industries we have called continuous processors underinvested in physical capacity and ended up having to lengthen actual plant workweeks substantially in order to meet higher than expected demand.

As we will discuss below, we can rule out this possibility by examining the survey data on capacity (output) utilization and factor utilization and the reported levels of factor inputs at capacity. However, to follow such a discussion requires an understanding of how the survey concept of capacity relates to the notions of technology and costs we discussed above.

Capacity Utilization and Factor Utilization

The capacity utilization concept focuses on how much feasible production capability is left, given a manufacturer's current, actual rate of output. Notationally, we let q_{jt} denote an operator that creates a utilization rate, the difference between a variable at the actual output level and that variable at the capacity output level. Also, we use lower-case variables to denote logarithmic form. Thus, for example, the (logarithmic) output utilization rate for plant j at time t is

$$(13) \quad q_{jt} = q_{jt} - q_{jt}^c,$$

where q_{jt} is the logarithm of actual output during the period, and q_{jt}^c is the logarithm of capacity output during the period. Similarly, h_{jt}^k and l_{jt} are the factor utilization rates for the work period and for labor intensity.

There are many possible theoretical definitions of capacity. We restrict our discussion to the capacity concept used in the Census SPC and Federal Reserve Board estimates of capacity utilization. We interpret the full-production capacity concept described in the survey questionnaires as basically equivalent to one of the capacity concepts defined by Klein (1960): capacity output is a full-input point on a production function.⁴ That is, capacity is a level of output attainable by "fully employing" the variable factors of production, given the current technology and keeping fixed factors at their current levels. Notationally, this could be written as:

$$(14) \quad Q_{jt}^c = \int_{m_{t-1}}^{m_t} f_{jt} \left(L_{jt}^c(m), K_{jt}^{cs}(m), R_{jt}^c(m); K_{jt}^c, N_{jt}^c \right) dm,$$

where the c superscripts denote the capacity values of the variables. For the definition of capacity to be complete, the full-employment level of the variable factor inputs needs

to be defined, and the distinction between variable and fixed factors needs to be precise.

In the Census SPC, respondents are explicitly told to consider the plant's stock of capital machinery and equipment, K_{jt} , to be a fixed factor, so $K_{jt}^c = K_{jt}$. More generally, if the short-run costs of adjusting a factor of production are sufficiently high, that factor is considered to be fixed at current levels for the purposes of determining capacity. For example, respondents are instructed to assume that at capacity the work period is constrained to "the number of shifts and hours of plant operation that can be reasonably attained by your plant in your community." We interpret this as a statement that if adding a third shift to a two-shift operation would entail relocating workers from other communities and paying correspondingly large hiring costs, such as moving expenses and housing supplements, then the configuration of the plant work period at capacity is two shifts. However, if the local labor market already has sufficient qualified workers to keep short-run recruitment and hiring costs for shift expansion low, then the capacity number of shifts can exceed the current number of shifts.

The survey instructions tell respondents not to consider overtime pay and added costs for materials to be limiting factors in estimating capacity. We interpret this as indicating that in assessing the level of factor inputs at capacity, respondents should not focus on the fact that static marginal costs (F_{jt} of equation (5)) can increase with the duration of the work period or volume of materials use, but rather should identify when sharply diminishing returns or high adjustment costs effectively place limits on factor inputs.

For example, for pure assemblers, changes to the line-speed (R_{jt}) and to labor intensity (L_{jt}) are postulated to trigger large adjustment costs. Hence, we would expect the capacity values of line speed and labor intensity to match their actual values. This would imply that when a pure assembly plant is open, the momentary output will be the same in actuality and at capacity, $\overline{f_{jt}} = \overline{f_{jt}^c}$. For such plants, the volume of capacity output would be proportional to the plant work period at capacity:

$$(15) \quad Q_{jt}^c = \overline{f_{jt}^c} H_{jt}^{Kc},$$

and all of the output utilization gap would be explained by differences between the actual and capacity configurations of the work periods:

$$(16) \quad q_{jt} = h_{jt}^k.$$

For pure continuous processors, changes to the flow rate of materials (R_{jt}) are postulated to have low adjustment costs, but changes to labor intensity (L_{jt}) and to any aspects of the work period (H_{jt}^K) are postulated to trigger large adjustment costs. Hence, we would expect the capacity values of the flow rate of labor intensity and the work period

4. The term "full production capacity" was introduced in the Census SPC for 1990 and represents only a slight modification of the capacity definition previously called the maximum "practical" level of output.

to match their actual values. The volume of production at capacity would be proportional to the plant work period at capacity:

$$(17) \quad Q_{jt}^c = R_{jt}^{c*} \overline{g_{jt}^c} H_{jt}^{kc},$$

with the factor of proportionality depending on the average flow rate of materials at capacity R_{jt}^{c*} and another term $\overline{g_{jt}^c}$ which depends only on factors such as labor intensity and the capital stock which are equivalent across actual and capacity configurations. Hence, for pure continuous processors, all of the output utilization gap would be explained by differences between the actual and capacity configurations of the instantaneous flow rate:

$$(18) \quad q_{jt} = r_{jt}^*.$$

Any evidence from the SPC which corroborates these strong implications of the postulated technological differences between continuous processors and variable work period industries serves to undermine the alternative explanation that technologies are identical but ex post differences in demand realizations have caused observed work period patterns to diverge across industries. As we will now discuss, some of these strong implications hold up relatively well.

In addition to capacity (output) utilization, the work period and labor intensity factor utilization rates are observable. To obtain individual output utilization rates from the microdata, we start with the observations on the volume of production V_{jt} , which is reported at current prices, P_{jt} :

$$(19) \quad V_{jt} = P_{jt} Q_{jt}.$$

Respondents are asked to use these same plant-specific prices in reporting the value of the volume of output at capacity, V_{jt}^c . Hence, the ratio of the reported variables on volume, V_{jt}/V_{jt}^c , also equals output utilization in real terms, Q_{jt}/Q_{jt}^c .

The SPC reports the number of production workers employed at the plant, N_{jt} , and also provides a corresponding measure of quarterly production worker labor hours, H_{jt}^L . Labor intensity, L_{jt} , is computed as the ratio of labor hours, H_{jt}^L , to the work period, H_{jt}^K . Respondents also report the capacity level of employment, N_{jt}^c , labor hours, H_{jt}^{Lc} , and components of the work period of capital H_{jt}^{Kc} . Accordingly, we can derive the utilization rates for the work period of the plants, h_{jt}^k , and labor (intensity), l_{jt} , from reported data. We do not observe materials flow intensity, r_{jt} .

Factor Inputs at Capacity by Industry Group

The capacity configuration of the work period factor inputs differs markedly by industry group (Table 2). Reflecting the initial criterion in our taxonomy, 91 percent of the

TABLE 2
ORGANIZATION OF THE WORK PERIOD AT CAPACITY
(PERCENT OF OBSERVATIONS IN GROUP)

	INDUSTRY GROUP			
	TOTAL MFG.	CONTINUOUS PROCESSING	VARIABLE WORK PERIOD	OTHER INDUSTRIES
WEEKS PER QUARTER (WEEKS ^c)				
<8	0.0	0.0	0.0	0.1
8-11	3.4	0.6	5.3	3.0
12	19.9	7.1	30.3	16.3
13	74.3	89.9	62.5	77.6
>13	2.4	2.3	1.9	3.0
DAYS PER WEEK (DAYS ^c)				
<5	0.3	0.0	0.4	0.4
5	41.1	3.1	57.8	49.3
6	23.7	6.0	30.7	28.8
7	34.9	91.0	11.2	21.4
SHIFTS PER DAY (SHIFTS ^c)				
1	9.8	0.3	10.9	16.0
2	24.8	6.8	36.1	24.0
3	65.4	92.9	53.0	60.0
HOURS PER SHIFT (LENGTH ^c)				
<8	6.8	0.8	10.4	6.8
8	81.2	92.8	74.8	80.6
>8	12.0	6.4	14.8	12.6
NUMBER OF OBSERVATIONS				
	16,812	4,311	7,215	5,286

See notes to Table 1.

plants in the continuous processing industries would run seven days per week at capacity. In contrast, only 11 percent of the plants in the variable work period group would operate every day of the week at capacity. Similarly, about 93 percent of the plants in continuous processing industries would run three eight-hour shifts per day at capacity, whereas only about 53 percent of the plants in variable work period industries would adopt this around-the-clock configuration for the capacity work period. Such differences in capacity configurations of the work period across

industry groups would be difficult to explain in terms of ex post differences in demand realizations.

Utilization by Industry Group

Patterns of factor utilization also differ markedly by industry group. First, it is clear that plants in the continuous processing industries almost always show no deviation from their capacity to run 24 hours a day, each day the plant is open (Table 3); only 3.1 percent of the continuous processing plants deviate from the capacity number of shifts per day, and 2.3 percent of the plants deviate from the capacity number of hours per shift. In contrast, about one-third of the plants in the variable work period group had the actual number of shifts deviating from the capacity number of shifts, and actual shift length also was out of line with capacity shift length about 22 percent of the time. Similarly, among plants in the continuous processing industries, actual operations were cut back one or more days from the capacity threshold for days only 11 percent of the time, but about 29 percent of plants in the variable work period group used this days-per-week margin for holding excess capacity.

For plants in the variable work period group, each of the *WEEKS*, *DAYS*, *SHIFTS*, and *LENGTH* margins is used with roughly equal frequency, between one-fifth and one-third of the time. At a given instantaneous flow rate of production, one would expect the magnitude of the effects on output utilization of using different work period margins to be roughly proportional to their effects on the work period itself. For example, for plants with thirteen weeks at capacity, we expect that shutting down for a week (losing one-thirteenth of the work period) would decrease actual output relative to capacity output by about one-thirteenth. Dropping a day from a six-day capacity workweek would decrease total hours one-sixth, other things equal, whereas decreasing the number of shifts from three to two shifts would reduce the work period by one-third. Given a modal shift length of eight hours, the impact on total hours of one-hour increments to shift length tend to be somewhat smaller than those of adjusting the work period by a day but larger than those of adjusting the quarterly work period by a week. Given these differential impacts of adjusting the various work period margins but relatively equal frequencies of use, we should expect shift utilization patterns to explain a lot of the variance in output utilization for plants in variable work period industries.

To pursue this idea, as well as to determine whether or not other aspects of equation (16) and equation (18) fit the data well, we turn to regression evidence. Table 4 displays the results of regressions that explain the plant-specific output utilization rates, q_{jt} , as a function of the utilization

TABLE 3
FREQUENCY OF USE OF DIFFERENT MARGINS FOR ADJUSTING WORK PERIODS IN MANUFACTURING (PERCENT OF OBSERVATIONS WITH NONZERO DEVIATIONS FROM CAPACITY)

	INDUSTRY GROUP			
	TOTAL MFG.	CONTINUOUS PROCESSING	VARIABLE WORK PERIOD	OTHER INDUSTRIES
WEEKS PER QUARTER (weeks 0)	15.2	10.3	20.2	12.3
DAYS PER WEEK (days 0)	23.2	11.1	28.7	25.6
SHIFTS PER DAY (shifts 0)	20.2	3.1	32.8	16.9
HOURS PER SHIFT (length 0)	14.5	2.3	22.5	13.5
NUMBER OF OBSERVATIONS	16,812	4,311	7,215	5,286

See notes to Table 1.

rates for labor intensity and the work period of the plant, either as a whole or with components of the work period entered separately. The orthogonal portion of the intensity of the flow rate of materials, r_{jt} , is left to the residual. Regressions omitting selected explanatory variables also were computed. We present the pattern of regression results as a decomposition of the variance in the dependent variable.

For total manufacturing, the regression results suggest that neither the pure assembler technology (equation (16)) nor the pure continuous processor technology (equation (18)) are adequate representations; variations in utilization of plant workperiods explain some, but not all, of the variance in output utilization. Also, changes in actual labor intensity relative to labor intensity at capacity explain about 25 percent of the variance in capacity utilization.

The results are more consistent with the implications of the pure technology types within the corresponding industry groups than within manufacturing as a whole. For plants in the continuous processing group, the residual unexplained variation is 63 percent, quite a bit larger than for the variable work period or other industries groups. This large residual variance suggests that orthogonal variations in the flow rate of materials and components are more important for continuous processors than for other manufacturers, as we expected. For continuous processors, most of the predictive power of the work period variable, h^k , is

TABLE 4

CONTRIBUTIONS TO VARIANCE IN OUTPUT UTILIZATION
(PERCENT OF VARIANCE)

INDUSTRY GROUP	CONTRIBUTIONS OF EXPLANATORY VARIABLES ^a						TOTAL EXPLAINED ^b	UNEXPLAINED
	<i>l</i>	<i>h^k</i>	COMPONENTS OF <i>h^k</i>					
			<i>weeks</i>	<i>days</i>	<i>shifts</i>	<i>length</i>		
TOTAL MANUFACTURING	25	37	4	6	27	3	62	38
CONTINUOUS PROCESSING	15	22	5	9	7	1	37	63
VARIABLE WORK PERIOD	27	41	5	5	32	1	68	32
OTHER INDUSTRIES	26	31	2	5	26	2	57	43

SOURCE: Calculations by the authors from the Survey of Plant Capacity microdata.

- NOTES: a. The entries are calculated from the R^2 of regressions of output utilization q on the explanatory variables. Each entry is the average of two estimates of the contributions of the regressors; one estimate is the difference between the R^2 of the full multivariate regression and a regression deleting only the explanatory variable shown at the head of the column, and the other estimate is the R^2 of a bivariate regression of output utilization on the explanatory variable. This process was repeated with h^k treated as a single variable and with only the components of h^k in the regressions. Note that this variance decomposition method does not constrain the sum of contributions to equal the total explanatory power.
- b. These regressions use observations from the 1979–1983 and 1984–1988 ASM waves. There are 16,812 observations for total manufacturing, 4,311 for continuous processors, 7,215 for plants in variable work period industries, and 5,286 observations for plants in other industries.

through use of the weeks and days margins, whereas within-day deviations from the (generally round-the-clock) configuration of operations at capacity are rare. The tendency to use shutdowns of days or weeks at a time instead of overnight suggests that the shutdown and startup costs are larger at continuous processors than in other industries.

Patterns of factor utilization among plants in the variable work period group look more similar to those implied by the pure assembler technology than to those implied by the pure continuous processor technology, but the pure assembler technology equation (16) does not fully describe the behavior of these plants. Variations in the work period of the plants are more important than variations in labor intensity and more important than residual flows for explaining short-run output adjustments among plants in the variable work period industries. Also, among the components of the work period, shift deviations have the largest explanatory power, likely reflecting the fact that plants in this group face relatively low overnight shutdown and startup costs. However, in contradiction to the implications of equation (16), actual labor intensity does not always equal labor intensity at capacity for these plants, and also

the residual flow is able to explain about 32 percent of the variance in capacity utilization.

In all three industry groups, manufacturing plants exhibit some positive correlation between output and utilization of each of three factors, the work period H^k , labor intensity L , and materials flow intensity R . One likely shortcoming of the stark dichotomy of technology types relates to aggregation. Individual components of the manufacturing process, such as a furnace or an individual assembly line, might be well-described by either the continuous processing or assembly model, but a manufacturing establishment can consist of many such components. For example, Bertin, Bresnahan, and Raff (1996) find that basic iron and steel production was well-described by a continuous processing model at the level of individual blast furnaces, but many plants had more than one blast furnace on site. By shutting down or starting up individual furnaces, an establishment that was a collection of continuous processing units could vary plant-level output without changing the flow rates of individual components or the work period of the plant as a whole. Similarly, some assembly operations are organized into “work stations” rather than assembly

lines. If each work station has low shutdown and startup costs, and the work stations can function independently of each other, then partial shutdowns can be used to vary output. This happens, for example, in apparel establishments that are merely a collection of sewing machines doing the same job. In both the case of an aggregation of continuous processing units and the case of an aggregation of assembly stations, the plant work period is a noisy measure of the actual work period of capital, and materials flow and labor intensity are likely to be positively correlated with the measurement error.

Changes over Time

Measurement error and omitted variables become even more important issues for analyzing changes in output and factor inputs over time using the SPC data. One major difficulty with estimating the volume production functions for either pure assemblers or continuous processors (equations (7) and (12)) is that the actual constant-dollar volumes of output Q_{jt} are not observed; we observe output volumes only in nominal terms, V_{jt} . Thus, we must focus on the revenue functions for pure assemblers and pure continuous processors, which are:

$$(20) \quad V_{jt} = \bar{f}_{jt} H_{jt}^K P_{jt} ,$$

$$(21) \quad V_{jt} = WEEKS_{jt} R_{jt}^* \bar{g}_{jt} 168 P_{jt} .$$

Unfortunately, plant-specific prices, P_{jt} , are not observed for each plant. Also, the proportionality factors (\bar{f}_{jt} for assemblers and \bar{g}_{jt} for continuous processors) which we would like to estimate as fixed parameters actually may differ across plants and over time. For example, technological improvements at a given assembly plant which shift its momentary production function, f_{jt} , would lead to an increased nominal volume of output even with an unchanged work period and prices.

We proceed, with the above duly noted caveat, under the simplifying assumption that, for a given plant, these proportionality factors do not change over time. Then, we focus on the logarithmic time difference forms of these equations to eliminate the proportionality factors:

$$(22) \quad v_{jt} = h_{jt}^K + p_{jt} ,$$

$$(23) \quad v_{jt} = WEEKS_{jt} + p_{jt} + r_{jt}^* .$$

Table 5 displays the results of regressions which nest these specifications by explaining the plant-specific nominal output changes, v_{jt} , as a function of changes in labor intensity and in the work period of the plant, either as a whole or with components of the work period entered separately. Also, an industry-level proxy for the plant-specific

price changes is included in each regression. Again, we present the pattern of regression results as a decomposition of the variance in the dependent variable.

The most striking feature of these regression results is the low explanatory power. The total explained variance for manufacturing as a whole is 17 percent. Subsample results for the variable work period group reveal only a little bit more explanatory power, 22 percent. We suspect that the poor goodness-of-fit largely owes to the inadequacy of changes in industry average prices to capture changes in plant-specific prices. Many manufacturing plants have a heterogeneous product mix which includes secondary products characteristic of other industries in addition to those products primary to the industry to which the plant is classified (Mattey and ten Raa 1997), and this heterogeneity diminishes the relevance of industry-based deflators. Also, even for individual products, dispersion of prices across plants can be quite large (Beaulieu and Mattey 1994). Another possible explanation for the low explanatory power of these regressions is that plant-specific technological changes tend to be quite large.

Given these caveats, it still is interesting to note that some of the basic implications of equations (22) and (23) show through in the subsample results for industry groups. With regard to continuous processors, equation (23) implies that the residual variation may be large, reflecting the presence of the additional term r_{jt}^* in the residual, and all of the explained variance should be accounted for by the contributions of changes in prices and in weeks of operation. In fact, the residual variance is large, and virtually all of the explained variance is accounted for by the contributions of changes in prices and in weeks of operation. With regard to the variable work period group, equation (22) implies that all of the explained variance should be accounted for by the contributions of changes in prices and in all components of the work period, possibly including major roles for within-week margins of work period adjustment. In fact, changes in the number of days-per-week, shifts, and shift-length do account for about one-half of the overall explanatory power. Among these, changes in the number of shifts are the most important. However, in contradiction to the pure assembler technology type, changes in labor intensity also account for about one-half of the overall explanatory power.

Next, we address the issue of whether there are major differences in how plants achieve capacity output adjustments over time which tend to corroborate or refute the hypothesis that plants in the continuous processor group face relatively large shutdown costs and plants in the variable work period group face relatively small shutdown costs. In addition to the work period of the plant at capacity, h_{jt}^{kc} , there are several other sources of potential variation in

capacity output suggested by its definition and our emphasis. These include changes over time in the stock of capital, K_{jt} , the flow rate of materials at capacity, r_{jt}^c , and the intensity of labor at capacity, l_{jt}^c . Substantial changes in either the work period at capacity, h_{jt}^{kc} , or the intensity of labor, l_{jt}^c , are likely to entail changes in the capacity level of employment, N_{jt}^c .

To summarize the extent to which capacity changes over time are due to changes in plant hours at capacity, h_{jt}^{kc} , versus changes in the capital stock, K_{jt} , labor intensity at capacity, l_{jt}^c , or the flow rate of materials at capacity, r_{jt}^c , we again look at contributions to the fit of regressions. Each regression has the form:

$$(24) \quad \dot{y}_{jt} = \alpha_0 + \alpha_1 h_{jt}^{kc} + \alpha_2 l_{jt}^c + \alpha_3 \hat{k}_{jt} + \alpha_4 p_t + \epsilon_{jt}$$

The dependent variable is the change over time in the plant's (logarithmic) level of nominal capacity output. The vector \hat{k}_{jt} contains four qualitative response variables indicating whether changes in the capital stock have changed capacity and four quantitative measures of changes in the capital stock. Changes in prices, p_t , are measured at the industry level. The flow rate of materials at capacity r_{jt}^c is not observable, and the orthogonal portion of r_{jt}^c and plant-spe-

cific price changes which differ from industry averages likely dominate the residual in the equation, ϵ_{jt} .

The proxies for changes in the capital stock included in the vector \hat{k}_{jt} are based on two types of measures. First, the capacity survey contains separate questions on why a respondent is reporting a change in capacity over time, including specific questions on changes in the capital stock. The variables on this portion of the survey are qualitative. Respondents can check one or more boxes indicating whether capacity has changed because of four types of changes in the capital stock, which cover expenditures and retirements of buildings and machinery separately.⁵ About 2.6 percent of the respondents indicate that building capital expenditures have led to capacity expansion, and 9 percent indicate substantial expenditures on machinery. Retirements occur much less frequently, at a 0.4 percent rate for build-

5. In addition to the four capital-related reasons for changing capacity, respondents also can indicate that capacity changes are from factors such as changes in the method of operation, product mix, or composition of material inputs. About 3 percent of respondents indicate capacity changes arise from changes in method of operation, and 2 percent cite material inputs. Product mix changes are widely cited, with about

TABLE 5
CONTRIBUTIONS TO VARIANCE IN CHANGES IN ACTUAL OUTPUT
(PERCENT OF VARIANCE)

INDUSTRY GROUP	CONTRIBUTIONS OF EXPLANATORY VARIABLES ^a							TOTAL EXPLAINED ^b	UNEXPLAINED
	l	h^k	COMPONENTS OF h^k				p		
			<i>weeks</i>	<i>days</i>	<i>shifts</i>	<i>length</i>			
TOTAL MANUFACTURING	7	7	2	2	4	0	3	17	83
CONTINUOUS PROCESSING	0	3	3	0	0	0	15	19	81
VARIABLE WORK PERIOD	11	10	2	3	6	1	0	22	78
OTHER INDUSTRIES	8	6	2	1	2	1	0	14	86

SOURCE: Calculations by the authors from the Survey of Plant Capacity microdata.

NOTES: a. The entries are calculated from the R^2 of regressions of logarithmic changes in nominal output y on the explanatory variables. Each entry is the average of two estimates of the contributions of the regressors; one estimate is the difference between the R^2 of the full multivariate regression and a regression deleting only the explanatory variable shown at the head of the column, and the other estimate is the R^2 of a bivariate regression of output changes on the explanatory variable. This process was repeated with h^k treated as a single variable and with only the components of h^k the regressions. Note that this variance decomposition method does not constrain the sum of contributions to equal the total explanatory power.
b. These regressions use observations from the 1979–1983 and 1984–1988 ASM waves. There are 5,707 observations for total manufacturing, 1,597 for continuous processors, 2,282 for plants in variable work period industries, and 1,828 observations for plants in other industries.

ings and a 1.8 percent rate for machinery. Overall, changes in the capital stock of at least one of these four types are reported as reasons for capacity changes for only about 11 percent of the observations.

Our second type of measure of changes in the capital stock is compiled by matching the SPC microdata with the microdata from the ASM. The latter survey includes quantitative estimates of new investment and retirements of machinery and buildings. We express these flow variables as a proportion of the book value of the corresponding type of capital (machinery or buildings) and let them serve as additional predictors of capacity changes.

The regression results are again summarized in terms of contributions to explaining the variance in the dependent variable, which in this case is changes in capacity output (Table 6).

These regressions also have low explanatory power, again likely due to the inadequacies of the price deflators or to a

13 percent of respondents indicating this as a source of capacity change. Because the direction of the impact on capacity of the changes indicated by these additional qualitative response variables is ambiguous, we have not included them in the analysis.

dominant role for technological change. Nevertheless, the subsample results show that for continuous processors, changes in the capital stock were the most important observable margin for adjusting capacity output (in real terms). Changes in the capacity labor intensity and work period explained almost none of the variation in capacity output. For plants in the variable work period group, changes in the capital stock also accounted for a noticeable fraction of capacity output changes. However, for plants in this group, changes in the capacity work period and labor intensity also were important.

The results on changes in capacity over time are interesting when viewed in conjunction with data on capacity utilization rates. Among plants in the continuous processor group, the mean capacity (output) utilization rate over the full sample period was 88 percent, which implies that such plants tend not to carry much excess capacity. In contrast, the mean capacity utilization rate for plants in the variable work period group was about 59 percent, which indicates that they tended to have a lot of room for upward expansion of output. Thus, in order to achieve large upward adjustments of actual output, continuous processors need to increase capacity, but plants in the variable work period group

TABLE 6

CONTRIBUTIONS TO VARIANCE IN CHANGES IN CAPACITY OUTPUT
(PERCENT OF VARIANCE)

INDUSTRY GROUP	CONTRIBUTIONS OF EXPLANATORY VARIABLES ^a				TOTAL EXPLAINED ^b	UNEXPLAINED
	l^c	h^{kc}	\hat{k}	p		
TOTAL MANUFACTURING	2.4	1.0	2.4	4.1	10.1	89.1
CONTINUOUS PROCESSING	0.5	0.0	3.6	14.1	18.2	81.8
VARIABLE WORK PERIOD	4.2	1.6	2.0	0.8	9.1	90.9
OTHER INDUSTRIES	2.0	2.1	2.7	1.5	8.5	91.5

SOURCE: Calculations by the authors from the Survey of Plant Capacity microdata.

NOTES: a. The entries are calculated from the R^2 of regressions of logarithmic changes in nominal capacity output ν on the explanatory variables measuring changes in labor intensity at capacity, l^c , changes in the work period at capacity, h^{kc} , proxies for changes in the capital stock, \hat{k} , and changes in industry-level prices, p . Each entry is the average of two estimates of the contributions of the regressors; one estimate is the difference between the R^2 of the full multivariate regression and a regression deleting only the explanatory variables shown at the head of the column, and the other estimate is the R^2 of a regression of output utilization on the explanatory variables at the head of the column. Note that this variance decomposition method does not constrain the sum of contributions to equal the total explanatory power.

b. These regressions use observations from the 1979–1983 and 1984–1988 ASM waves. There are 8,795 observations for total manufacturing, 2,378 for continuous processors, 3,671 for plants in variable work period industries, and 2,739 observations for plants in other industries.

generally do not need to increase capacity. Thus, the capacity change regression results suggest that plants in the continuous processor group basically only have two margins for large expansions of output, engaging in physical investment in plant and equipment or improving technology. However, many plants in the variable work period group have additional margins, such as adding a shift and hiring additional employees to staff it.

III. HOW THIS HELPS RESOLVE PUZZLES

So far in this paper, we have presented theoretical examples of how technological differences among manufacturing plants could give rise to varying patterns of factor utilization which affect the relationships between costs and output changes. We also have shown that empirical evidence is consistent with the existence of some actual manufacturing plants with technologies resembling each of the theoretical extremes, “pure continuous processors” and “pure assemblers,” but the use of workweek margins as in the assembler type appears to have more relevance than continuous processing in the aggregate. The recognition of these patterns helps resolve some puzzles in the economics literature.

Capacity Utilization, Marginal Costs, and Prices

Other things equal, an increase in capacity utilization at a manufacturing plant is likely to be associated with an increase in its output price, given that capacity is invariant in the short-run, and assuming that output is increasing because the demand curve has shifted outward along an upward-sloping supply (marginal cost) curve. Alternatively, economic theory admits the possibility of a negative correlation between capacity utilization and price changes if the output increase is along a downward-sloping portion of the marginal cost curve. In terms of empirical evidence, capacity utilization is useful as an aggregate indicator of inflationary pressures (Corrado and Matthey 1997), but Shapiro (1989) is among those who have noted that the data do not universally support the simple notion that output utilization increases signal outward movements along upward-sloping marginal cost curves. Given also Shea’s (1993) findings, the balance of evidence seems to support relatively sharply upward-sloping marginal cost curves in continuous processing industries, but there is greater uncertainty about the slope of marginal cost curves in variable work period industries.

Our findings in this paper that there appear to be large differences between continuous processing industries and variable work period industries in how output adjustments are achieved provide a consistent framework for under-

standing this pattern of empirical results on capacity utilization and price changes. To the extent that plants in variable work period industries have technologies which represent the “pure assembler” archetype, they face decreasing marginal costs over some ranges of output changes and increasing marginal costs over other ranges of output changes. In particular, a plant which adds a shift incurs an adjustment cost but also triggers decreasing marginal costs over the range of output where the shift would be quite understaffed. This non-convexity in marginal cost curves is not present in continuous processors because the shift margin is not available to them.

Workweek of Capital and Productivity Growth Accounting

Many economists have puzzled over why estimates of total factor productivity growth tend to be very procyclical. Although shifts in aggregate demand are thought by many to be the prevailing source of business cycle fluctuations, estimates often show that total factor productivity growth picks up when output is expanding, and productivity growth slows in contractions, as if exogenous technological fluctuations were driving the fluctuations in output.

Recent contributions to the literature on capital utilization note that the appearance of strongly procyclical productivity could owe to the mismeasurement of changes in capital service flows. In periods of high capital utilization, the flow of services from the capital stock is likely to be underestimated, and total factor productivity overestimated, if capital service flows are assumed to be proportional to capital stocks. Data on capital utilization could help one overcome this measurement difficulty.

The problem is that capital utilization per se is not observable. Materials and energy usage have been used as proxies for capital utilization by some authors (e.g., Basu 1996 and Burnside, Eichenbaum, and Rebelo 1995), whereas the workweek of capital has been emphasized as the best capital utilization proxy by others (Shapiro 1986, 1993, 1996, Beaulieu and Matthey 1995).

The models and empirical evidence discussed in this paper help us discriminate between these alternative choices for capital utilization indicators. In particular, the workweek of capital is a perfect indicator of capital utilization for any plant with a pure assembler technology type (equation 7). In contrast, pure continuous processors do not use the workweek margin, so the workweek should not be used as an indicator of capital utilization for such plants. In our heuristic derivation of a simplified production function for continuous processors (equation 12), we also have assumed that the instantaneous speed of capital, the $s_{jt}(m)$ of equation (1), is invariant. However, more generally continu-

ous processors could exhibit variations in the speed of capital, likely in proportion to the momentary flow rate of materials and other intermediates $R_{jt}(m)$. In this case, the average flow of materials R_{jt}^* during the quarter would be a perfect proxy for capital utilization at continuous processors. Our empirical evidence suggests that although one cannot perfectly segregate actual manufacturing industries into such pure technology groups, the data do support some bifurcation along these lines.

Shapiro (1996) has studied the workweek data from the SPC as aggregated from the plant to industry level by Beaulieu and Matthey (1995). Shapiro found that in terms of reducing the appearance of procyclicality in total factor productivity growth, the plant workweek data are superior to materials and energy usage proxies for noncontinuous processor industries. For continuous processor industries, the materials and energy proxies are superior to the workweek as a measure of capital utilization. Shapiro's (1996) findings are consistent with the theoretical models of technology types presented here and with our demonstration that the classification of actual industries into such technology groups is not strongly rejected by the data.

IV. CONCLUSION

Recent literature suggests that the relationships between marginal costs and output levels of manufacturers are complicated by the presence of multiple ways to achieve output changes and of one-time costs to adjusting some factors of production. A related literature also emphasizes the need to account for changes in the work period of capital in studying the cyclicity of productivity growth. This paper explains the basic issues in these literatures and develops new evidence on the relevance of their concerns about heterogeneity in patterns of factor utilization, drawing from previously unstudied individual responses to a survey of manufacturing plant capacity and factor utilization. We find that the concerns about the heterogeneity in patterns of factor adjustment are well-founded. Plants in some industries appear to face sizeable shutdown and startup costs which prevent them from using within-week plant work period changes as a margin of adjustment. Plants in many other industries exhibit substantial variations in plant workweeks over time. For manufacturing as a whole, the workweek appears to be a significant margin of adjustment.

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A New Look at the Distributional Effects of Economic Growth during the 1980s: A Comparative Study of the United States and Germany

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Beginning in 1983, and following the worst recession since the Great Depression, the United States experienced six years of uninterrupted economic growth, the longest such period since World War II. Along with this expansion came an increase in income inequality that many suggest diminished the middle class and made the United States unique among industrialized nations in its pace of economic growth and increase in income equality.

This paper addresses these issues by using kernel density estimation to document changes in the United States income distribution during the 1980s economic expansion and to compare these changes to those experienced in Germany. The findings confirm that income inequality did increase and the United States middle class did lose members during the 1980s. However, these outcomes were due largely to real income gains rather than real income losses. The comparative analysis shows that these patterns were similar to those observed in Germany.

For over 25 years following World War II, the benefits of economic growth were distributed more or less uniformly throughout the income distribution. In 1973, however, the gains from economic expansions began to flow more heavily toward the top of the distribution, increasing income inequality, diminishing the middle class, and raising concerns that the link between economic growth and broad based prosperity had been broken (U.S. Bureau of the Census 1991; Karoly 1993; Easterlin, MacDonald, and Macunovich 1991). As the last decade of the 20th century began, these concerns intensified. Despite six years of sustained economic expansion, the decade of the 1980s closed with a higher degree of income inequality, a larger number of individuals in poverty, and a smaller portion of the population in the middle of the income distribution than had been there at its beginning. In combination, these circumstances struck a nerve among policymakers, researchers, and the public alike, and prompted many to ask whether the government should take a more active role in guaranteeing the equality of outcomes among the population.

At the heart of this questioning were two suspicions. The first was that the increases in poverty and inequality and the decline in the middle of the distribution were linked, implying that economic growth was benefiting only the wealthiest of the population (Duncan, Smeeding, and Rodgers 1992; Karoly and Burtless 1995). The second was that the increase in inequality and the decline in the middle of the distribution were outcomes unique to the United States and not experienced in industrialized nations with more intervention-oriented economic policies (Burtless and Smeeding, 1995).

In many ways research on the changing patterns of the United States income distribution during the 1980s lends credence to these suspicions.¹ The large body of research on the United States income distribution shows that income inequality increased in the United States during the last decade and suggests that these changes diminished the middle class and left the “vulnerable” more exposed to economic losses due to a weakened social safety net (Karoly and Burtless 1995; Karoly 1993; Duncan, Smeeding, and Rodgers 1992). The international literature indicates that

1. See Levy and Murnane (1992) and Karoly (1993) for a review of this literature.

while inequality has grown in other western industrialized countries throughout the 1980s, the United States had the highest level of income inequality (Gottschalk and Smeeding forthcoming).

These images of the patterns of inequality in the United States during the last decade and their relationship to those in other industrialized countries are based almost entirely on parametric measures, such as the Gini or Theil coefficients, which summarize information about the income distribution into a single number. While these measures provide useful indications of changes in the overall income distribution, a richer picture of the 1980s can be seen by comparing changes in the entire income distribution over the period. This can be done using a statistical technique known as kernel density estimation to draw a picture of the distribution of income for each country in each year of the period. The benefit of this technique is that it provides a direct means of examining where changes in the distribution of income have occurred and whether the changes are similar or different across countries.²

Using kernel density estimation, this paper first examines the effects of 1980s economic growth on the distribution of income in the United States. To assess whether the experience of the United States was unique, the United States outcomes are compared to outcomes in Germany, a country with significantly lower levels of inequality, an explicit commitment to preserving the relative economic status of its citizens, and an economic and political experience during the 1980s that mirrored that of the United States.³

This paper first describes the influence of the 1980s economic expansion on the level and character of inequality in the United States. The paper then examines whether the outcomes realized in the United States were unique by comparing outcomes in the United States and Germany. Such a comparison can determine whether the disparate inequality profiles for the United States and Germany are representative of real differences in the impact of the 1980s economic expansion on the populations of the two countries or whether they are the result of the measurement tools used to characterize income distributions. Furthermore this comparison provides information about the extent to which explicit commitments to relative income equality, like the ones made in Germany, equalized the gains and losses experienced by various sub-populations during the 1980s.

2. See Burkhauser, Crews, Daly, and Jenkins (1996), DiNardo, Fortin, and Lemieux (1996), Ginther (1995), and Jenkins (1995) for examples of analyses of income and earnings distributions using kernel density estimation.

3. For a complete examination of these changes, see Smyser (1993).

I. METHODOLOGY

Estimation Methods

There are a variety of ways in which information about the changing shape of income distributions can be summarized. Traditionally this has been done with parametric summary measures, such as Gini or Theil coefficients, or with fixed-width histograms, which rely on a small number of class distinctions. These measures capture some information about broad changes in the population income distribution, but they are less effective in providing details of how individuals at all income levels are affected over time. Moreover, there is no consensus about the appropriate parametric measure or the number and sizes of the classes to use, and the empirical findings are often sensitive to the methods chosen.

Kernel density estimation is an attractive alternative to traditional summary statistics or graphical methods for measuring income inequality. It provides a picture of the entire distribution in terms of the income frequency density function, from which the distribution's level, modality, and spread can be observed simultaneously. These characteristics make kernel density estimation an ideal method for identifying the links between economic growth and income inequality.

The kernel density approach is a formal method of fitting a curve to an empirical frequency distribution. In their simplest forms, kernel estimators are much like smoothed histograms: data in a neighborhood around a point are used to estimate the distribution of a variable of interest (e.g., income) over a population. However, while histograms restrict observations to fall into only one neighborhood group, kernel estimators allow an observation to be included in several neighborhood groups, which results in a smoothing of the distribution shape.

A kernel density estimator can be thought of as a viewing window that slides over the data. The estimate of the density depends on the number of observations that fall within the window as it passes along the income scale. A simple example of such an estimator is one which uses a window of data with half-width (or bandwidth) h_n , and, for each point in the sample, the density estimate is equal to the number of points that fall in the interval $(-h_n, h_n)$ centered on the point. The density is then scaled by the number of observations and the width of the window. For a sample of size n , the estimator just described for the point x_i has the form

$$\hat{f}_n(x_i) = \frac{1}{n} \frac{1}{2h_n} \{\text{number of } x_1, \dots, x_n \text{ falling in } (x_i - h_n, x_i + h_n)\}.$$

If a weighting function W is defined such that $W(t) = 1/2$ if $t < 1$, and 0 otherwise, then the estimator may be written as

$$\hat{f}_n(x_i) = \frac{1}{n} \prod_{j=1}^n \frac{1}{h_n} W \left(\frac{x_i - x_j}{h_n} \right).$$

The weighting function W is a member of the class of functions known as kernels, where kernel refers to the rule used to assign weights to the observations. The only restriction on a kernel function, K , is that it integrates to 1 over the range covered by the distribution. Any probability density function satisfies this condition. The kernel density estimator has the same differentiability properties as the kernel function chosen. Although K is often symmetric, the resulting density estimate does not inherit this characteristic.

For consistency of the kernel estimator, the bandwidth h_n should decrease as the sample size increases. Choosing an optimal bandwidth is difficult to do, however, because the data vary in sparseness over the range of the distribution, and setting a bandwidth based on the sparse data areas will lead to oversmoothing in the denser areas. Ideally, the bandwidth should respond to the amounts of information at different points in the distribution, becoming narrower in dense parts of the distribution (the middle) and wider in sparse parts (the tails). This feature is obtained by using adaptive bandwidths which vary with the amount of information available.

One way to calculate adaptive bandwidths is to use a two-stage procedure that relies on pilot estimates of the density, obtained from fixed bandwidth estimates, to calculate bandwidth weighting factors. These weighting factors are then used to adjust the bandwidths over the range of the data. The factors, w_i , are defined as

$$w_i = \sqrt{\frac{\frac{1}{n} \sum_{j=1}^n w_j \log \tilde{f}_n(x_j)}{\tilde{f}_n(x_i)}},$$

where $\tilde{f}_n(x)$ is the pilot estimate of the density. The adaptive kernel density estimator for the point x_i is then

$$\hat{f}_n(x_i) = \frac{1}{n} \prod_{j=1}^n \frac{1}{h_n} w_j K \left(\frac{x_i - x_j}{h_n} \right),$$

where the weighting function W has been replaced by the more general form K , and the weighting variable w_j is included to account for sample design. The estimator \hat{f} is the kernel density estimator used in the analysis. The kernel

function used in this analysis is the Epanechnikov kernel function.⁴

II. YEAR SELECTION, DATA, AND VARIABLE DESIGN

Business Cycles and the Income Distribution

Although most economists take for granted that any examination of changes in the income distribution over time will be sensitive to the years being considered, research in this area has frequently failed to distinguish between changes associated with movements in the business cycle and changes that occur between two similar points in the business cycle (Burkhauser, Crews, and Daly, forthcoming). While there are no formal rules for choosing comparison years, Figure 1 illustrates the potential problem with selecting analysis years randomly. Figure 1 shows median real family income in the United States over the past twenty-five years. If one were to compare median real income in 1979 and 1992, one would get the impression that the decade of the 1980s left the median American worse off.⁵ However, 1979 is a peak year and 1992 is a trough year of two different business cycles. Looking peak to peak (1979–1989) in Figure 1 a very different impression emerges. Median real income actually rose by almost \$3,000 during this period. This simple exercise confirms the common sense notion that income distribution comparisons are sensitive to business cycle fluctuations and underscores the importance of careful year selection.

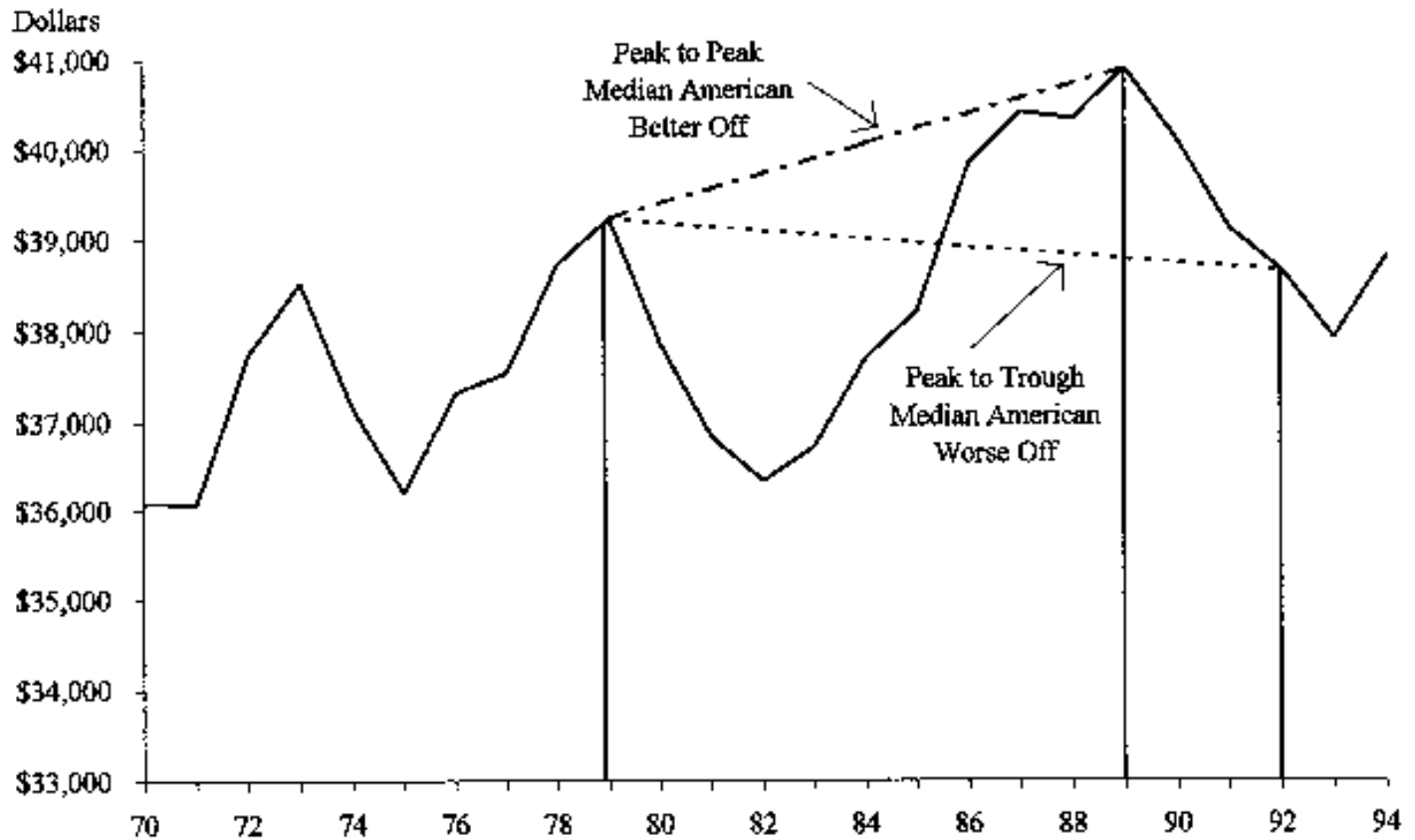
Figure 2 plots real Gross Domestic Product (GDP), real personal income growth, and the unemployment rate for both the United States and Germany. The top panel of Figure 2 shows that the United States economy experienced a serious recession in the early part of the 1980s, with unemployment peaking at post-World War II highs in 1982. This was followed by substantial economic growth and falling unemployment rates for the rest of the 1980s. Like the United States, Germany experienced a recession in the early 1980s as well as a strong economic recovery through the rest of the decade. However, the unemployment rate,

4. The reported results are not sensitive to the choice of kernel functions. See Burkhauser, Crews, Daly, and Jenkins (1997) for results using the normal kernel function.

5. Danziger and Gottschalk (1995), Burtless (1996a, 1996b) and Karoly (1996) comparing these years have characterized the 1980s as a decade in which “the rich got richer and the poor got poorer.”

FIGURE 1

REAL MEDIAN FAMILY INCOME IN THE UNITED STATES, 1970–1994



which was below that of the United States at the start of the decade, was higher throughout the second half of the decade.

Data constraints for Germany make peak-to-peak comparisons impossible. However, data are available to examine the first and last years of economic expansion in each country. The selected years are marked by vertical lines in Figure 2. In the United States 1983 and 1989 are used; in Germany 1984 and 1991 are chosen. These years approximate the points at which all three measures, real GDP, real personal income, and unemployment pointed to the beginning and end of economic expansion.

Data

The two data sets used in this study are the 1990 Response-Nonresponse File of the United States Panel Study on Income Dynamics (PSID), including the SEO over-sample of low-income people and the 1997 Syracuse University English Language Public Use File of the German Socio-

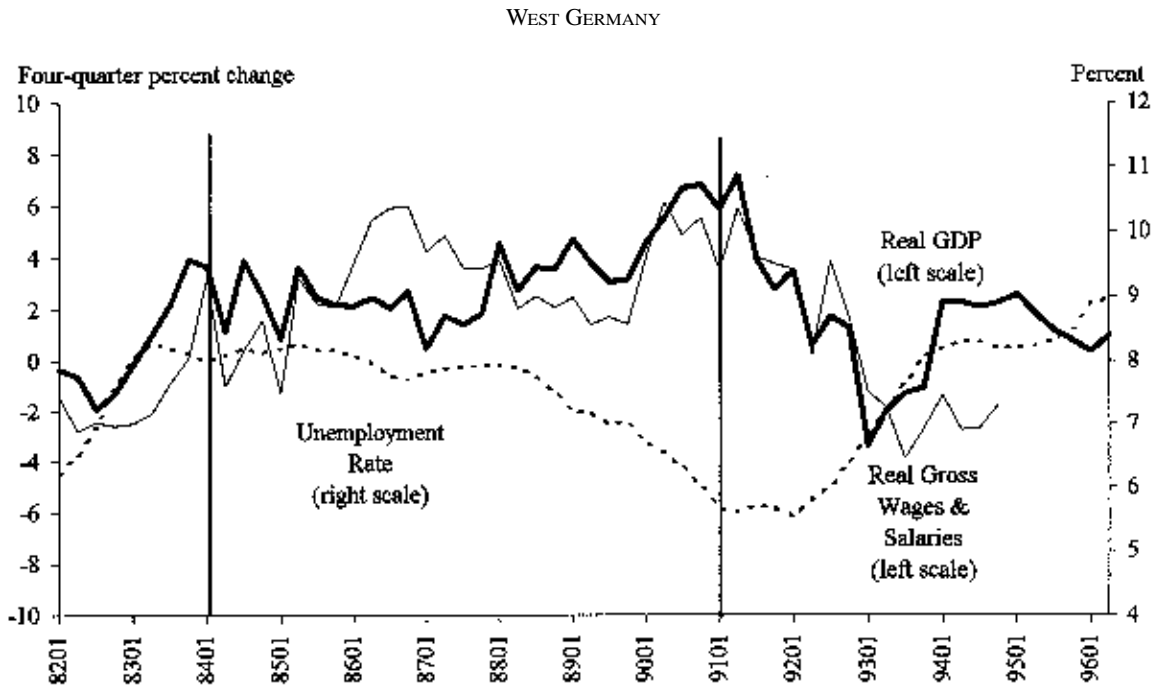
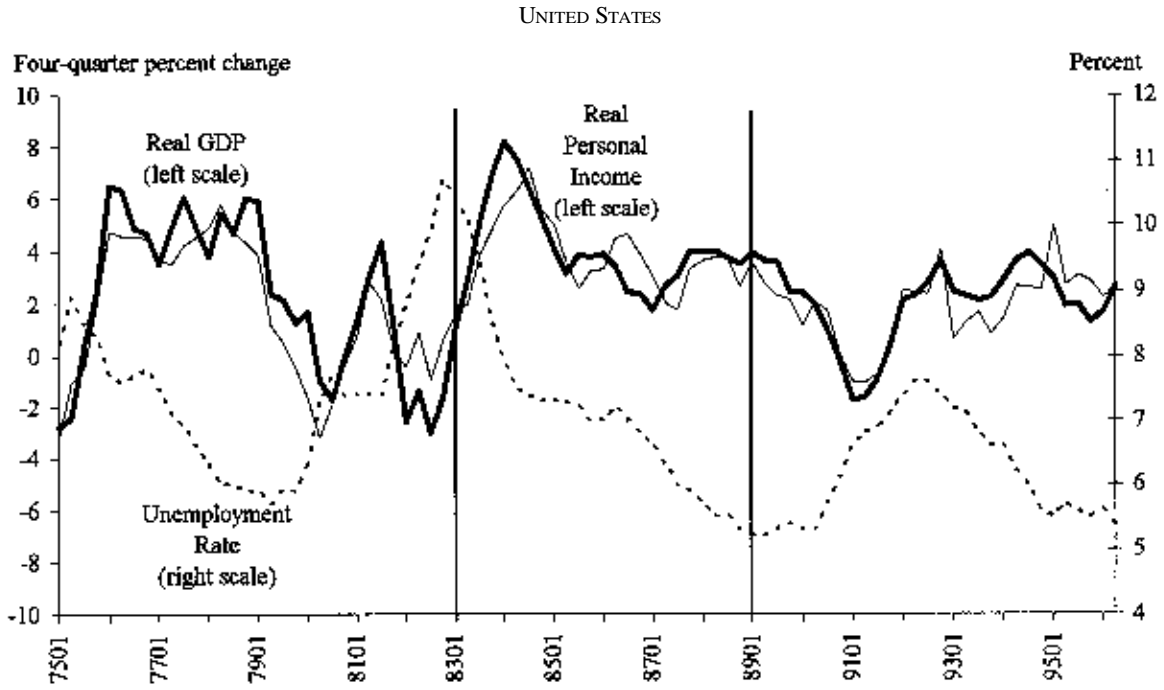
Economic Panel (GSOEP)⁶. Selected years of these surveys were chosen to capture the first and last complete year of the economic expansion during the 1980s. In the United States, survey years 1984 and 1990 were selected; in Germany survey years 1985 and 1992 were selected. These survey years correspond to income flows for 1983 and 1989 in the United States and 1984 and 1991 in Germany.

The PSID data span over two decades from 1968 to 1989. The panel began with a sample of 5,000 families, including a disproportionate number of low-income families. As of 1990 the PSID contained information on more than 35,000 individuals, approximately 20,000 of whom were

6. In the United States, cross-sectional analyses of this type typically use data from the Current Population Survey. However, since Germany does not produce an equivalent to the CPS, this analysis uses PSID data which are comparable in design, sample size, and content to data from the GSOEP. In comparative work, data from the PSID and CPS have been shown to produce equivalent results; see Burkhauser, Crews, Daly, and Jenkins (1996) and Burkhauser and Crews (1997) for examples.

FIGURE 2

THE UNEMPLOYMENT RATE AND REAL GROWTH IN GROSS DOMESTIC PRODUCT AND PERSONAL INCOME IN THE UNITED STATES AND GERMANY



current respondents. The remaining 15,000 individuals are currently nonrespondents but have participated in the survey at some time. Non-sample individuals, unrelated by marriage or birth to one of the original 5,000 families, are excluded from the analysis. The PSID does not provide sampling weights for these individuals, and therefore they cannot be included in our analysis.⁷

The GSOEP began in 1984 with a sample of 6,000 families including a disproportionate number of non-German "guest-workers." The GSOEP currently contains data on approximately 6,000 families and nearly 14,500 individuals. Although the GSOEP now includes data on those living in the former German Democratic Republic, in this study the analysis is restricted to those living in states of the Federal Republic of Germany prior to reunification.⁸ Although both the PSID and GSOEP are panel surveys, in this analysis they are treated as annual cross sections. Thus, no attempt is made to follow individuals over time. Both data sets can be weighted to represent their respective populations. The appropriate weights are applied throughout the analyses.

Measuring Economic Status

Because most people share resources within families, the family is usually considered the appropriate unit for collecting information on economic status. That approach is followed here. A family is defined as all individuals living in a household who are related by blood or marriage or who are cohabitating. Unrelated individuals sharing resources as roommates are treated as individual single-person families. To ensure that the cross-national comparison captures differences in outcomes that are allowed to prevail in both countries, this paper uses family post-tax post-transfer money income which includes in-cash government transfers and federal income and employment taxes.⁹ Family income is calculated by summing the sources of income

7. For a more detailed discussion of these data see Hill (1992).

8. For a more complete discussion of these data, see Wagner, Burkhauser, and Behringer (1993).

9. The tax burden for families in the GSOEP was computed using tax calculation routines first developed by Johannes Schwarze of the Deutsches Institut für Wirtschaftsforschung. A detailed discussion of the simulations is found in Schwarze (1995). For the United States the tax routine was provided in the PSID data. In both the United States and Germany the tax models ignore local and state taxes on property or income. Sales taxes are also ignored. Tax-adjusted values for both data sets are available in the Syracuse University Panel Study of Income Dynamics and German Socio-Economic Panel Equivalent Data File. See Burkhauser, Butrica, and Daly (1995) for a detailed discussion of these data.

for all family members during a calendar year. To obtain a more comprehensive income measure, the in-cash value of food stamps is added in the United States, the imputed rental value of owner-occupied housing is included in the United States and Germany, and the value of housing benefits is counted in Germany.¹⁰ All incomes are converted to 1991 dollars using the CPI-UX1 in the United States and to 1991 deutsche marks using the IMF Consumer Price Index in Germany.¹¹

There are many reasons why family income is less than an ideal measure of economic status (Moon and Smolensky 1977). One of the most important is differences in family size. To account for the fact that \$200 a week provides a higher standard of living for a single-person family than it does for individuals belonging to larger families, the family income measure is deflated by an equivalence factor. Since there is no universally accepted equivalence scale, one commonly used by cross-national researchers (Burkhauser, Smeeding, and Merz 1996) which has an elasticity of 0.5 is applied.¹² An elasticity of 0.5 assumes the median value of the potential returns to scale (ranging from 0 to 1) is operative.

III. INEQUALITY AND ECONOMIC EXPANSION

Before discussing findings from the kernel density estimation, we present the results from parametric measures of economic well-being and inequality in Table 1. Among the most utilized measures of income inequality is the Gini coefficient. The Gini is a measure of relative income inequality constructed by comparing the degree to which

10. The PSID does not record cash transfers specifically for housing, nor does it provide an estimate of the cash value of government provided housing. No attempt is made to impute a value for this variable, since housing related transfers represent a small fraction of the overall transfer benefits provided to needy citizens.

11. Burkhauser, Crews, and Daly (forthcoming) show that income distribution analysis is sensitive to the price index selected. The indexes selected for this analysis are both standard in the literature and thought to overstate, rather than understate, inflation. Thus, an alternative index would most likely strengthen the results reported here.

12. Equivalence scales contain assumptions about the returns to shared living. An equivalence scale with an elasticity of 1 would imply that two individuals living together require twice as much income to be equally well-off. Equivalence scales with an elasticity of 0 assume that a household with an infinite number of individuals can live equally well off the income of a single person household. Thus, an elasticity of 0.5 assumes that the true economies of scale lie directly in between these two extreme values. See Burkhauser, Smeeding, and Merz (1996) for a discussion of the sensitivity of different equivalence scales in cross-national comparisons.

TABLE 1

SUMMARY MEASURES OF FAMILY SIZE-ADJUSTED INCOME INEQUALITY FOR INDIVIDUALS IN THE UNITED STATES AND GERMANY

	ALL PERSONS					
	UNITED STATES			GERMANY		
	1983	1989	PERCENT CHANGE	1984	1991	PERCENT CHANGE
GINI	0.352	0.383	8.8	0.279	0.280	0
90/10 RATIO	5.72	6.23	8.9	3.33	3.54	6.3
90/50 RATIO	2.07	2.19	5.8	1.73	1.83	5.8
50/10 RATIO	2.76	2.81	1.8	1.92	1.94	1.0
MEDIAN FAMILY SIZE-ADJUSTED INCOME	\$17,761	\$19,663	10.7	DM25,154	DM29,897	18.9
MEAN FAMILY SIZE-ADJUSTED INCOME	\$20,581	\$23,885	16.1	DM27,763	DM33,123	19.3
STANDARD DEVIATION OF FAMILY SIZE-ADJUSTED INCOME	\$15,736	\$22,956	45.9	DM17,062	DM18,871	10.6
SAMPLE SIZE	6,918	7,328	NA	5,043	4,391	NA

Post-transfer, post-tax family size-adjusted income per individual in 1991 dollars based on data from the *Panel Study of Income Dynamics*.

Post-transfer, post-tax family size adjusted income per individual in 1991 DM based on data from the *German Socio-Economic Panel*.

income is proportionally distributed throughout the population. When income is distributed equally the Gini coefficient equals 0; thus higher values of the Gini index represent higher degrees of inequality. A second set of measures reported in Table 1 are percentile point measures. These measures calculate the absolute difference in the level of income held by individuals at different percentiles of the population.¹³ Table 1 reports values for three such measures: the 90/10, 90/50, and 50/10.

Inequality in the United States is substantially higher than in Germany. Moreover, while the Gini coefficient increased by 10 percent in the United States between 1983 and 1989, it remained constant in Germany. However, because the Gini coefficient summarizes movements in the entire income distribution in a single number, it cannot detect the movements within the distribution hinted at by the three percentile point measures. Moreover, since the Gini measures relative rather than absolute inequality, findings between the two types of measures may differ. Over the expansion period studied for each country the 90/10 measure grew by 8.9 percent in the United States, and by 6.9 percent in Ger-

many. Most notably, in both countries increases in the 90/50 measure outpaced growth in the 50/10 measure, implying a larger increase in dispersion at the high end of the income distribution than at the low end.¹⁴

Overall, the results reported in Table 1 illustrate some of the difficulties of relying on single summary measures of inequality to characterize changes in an entire distribution. While they provide useful information, by definition they constrain the analysis to just one parameter. The percentile point measures are more flexible, but force the researcher to specify particular points a priori. In contrast, kernel density estimation records the relative concentration of individuals at each income level without any parametric specifications or assumptions and provides a straightforward method of comparing changes in these concentrations over time.

IV. VIEWS OF THE INCOME DISTRIBUTION USING KERNEL DENSITY ESTIMATION

The remaining analysis uses kernel density estimation to provide pictures of the entire distribution of income in

13. The formulas for computing the Gini index and the various percentile point measures are provided in the Appendix.

14. See Gottschalk and Smeeding (forthcoming) for similar results using data from the Luxembourg Income Study.

each year under study. Estimates of the income frequency density functions for the full population of the United States in 1983 and 1989 are shown in Figure 3. As Figure 3 reveals, the economic expansion affected both the shape and position of the income distribution. Comparing the 1983 and 1989 curves shows that economic growth improved the economic fortunes of nearly the entire population while increasing income inequality. The figure shows that for a large fraction of the population, economic growth translated into increases in economic well-being. However, for a small proportion of the population, economic well-being declined between 1983 and 1989, a point demonstrated by the portion of the 1989 curve lying to the left of the 1983 graph. Such shifts in the income distribution during an economic expansion are not particularly surprising and have been documented in the literature.

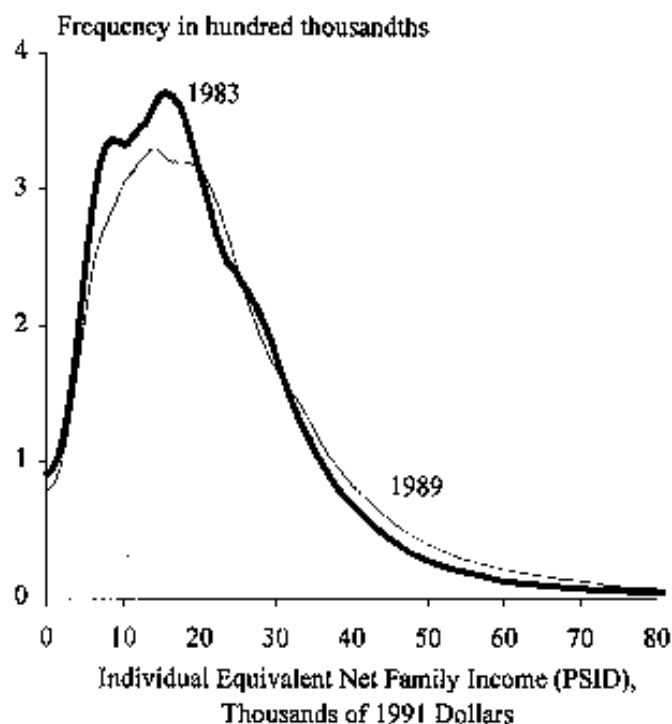
What is less well-known is the extent to which the 1980s expansion altered the shape of the income distribution. Figure 3 shows that in addition to lying to the right of the 1983 distribution, the income distribution in 1989 is shorter, wider, and has a thicker right tail. During the expansion

period the proportion of the population in the middle of the income distribution declined, pushing mass into the tails of the distribution and increasing income inequality. However, as Figure 3 illustrates, this displacement of the middle mass did not flow equally into the lower and upper parts of the distribution. The vast majority of the lost middle slid to the right, representing an improvement, rather than a decline, in economic well-being. The figure shows that although income inequality rose during this period, it was not because the rich got richer and the poor and the middle income groups became worse off, but rather because a significant fraction of the middle mass fell to the right while a small proportion of the population remained stuck at the bottom.

Figure 4 portrays a similar situation for Germany in 1984 and 1991. The large hill in the middle of the distribution in 1984 fell mostly forward, substantially increasing the right side of the hill. As in the United States, the shift in concentration away from the middle was asymmetric. The increase in the density within the higher income groups was larger than the increases in the lower

FIGURE 3

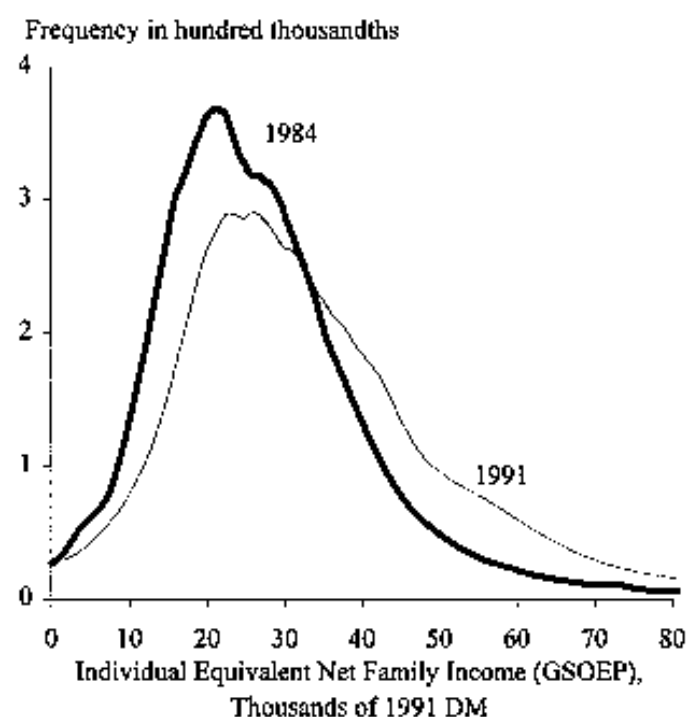
THE INCOME DISTRIBUTION IN THE UNITED STATES
IN 1983 AND 1989: CROSS-SECTIONAL DATA
(TOTAL UNITED STATES POPULATION)



SOURCE: Authors' calculations based on PSID (1984 and 1990)

FIGURE 4

THE INCOME DISTRIBUTION OF GERMANY
IN 1984 AND 1991: CROSS-SECTIONAL DATA
(TOTAL GERMAN POPULATION)



SOURCE: Authors' calculations based on GSOEP (1985 and 1992)

income ranges. Thus, as in the United States the increased income inequality that accompanied economic growth was associated with increases in absolute economic well-being for most of the population.

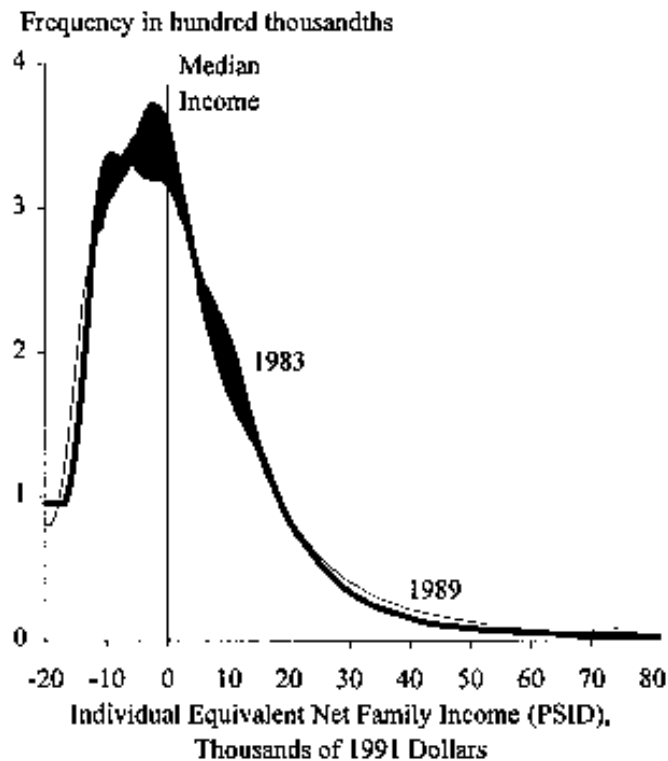
To verify that the inequality findings in Figures 3 and 4 are robust, Figures 5 and 6 show the same distributions normalized by median income in each year. Comparing these median preserving distributions of income in the United States and Germany verifies that economic expansion increased the dispersion in the income distribution of each country. In both the United States and Germany the middle mass of the income distribution diminished, and the mass in the left and the right tails increased. Thus, while economic recovery improved the absolute position of almost all members of the population (as demonstrated in Table 1 and Figures 3 and 4), in relative terms some portions of the population benefited more than others. The next section investigates which sub-populations reaped the largest benefit from the 1980s expansion.

V. THE EFFECTS OF EXPANSION ON POPULATION SUB-GROUPS

To better understand how certain sub-groups within the population were affected by the decade of the 1980s, the population is divided into persons living in three types of families. The division is based on the age and labor market connection of the primary adults in the family, defined as the head and, if relevant, the spouse or partner. The first group includes all persons who live in families in which the primary adults are younger than age 60 and at least one works in the labor market. The second group includes all families with at least one primary adult aged 60 or older; this categorization captures retired workers and their families, most of whom rely on social insurance and private pensions for their income support. The third group contains persons living in non-aged families in which no primary adult is working in the labor market; this final group includes families most likely to rely on some form of social

FIGURE 5

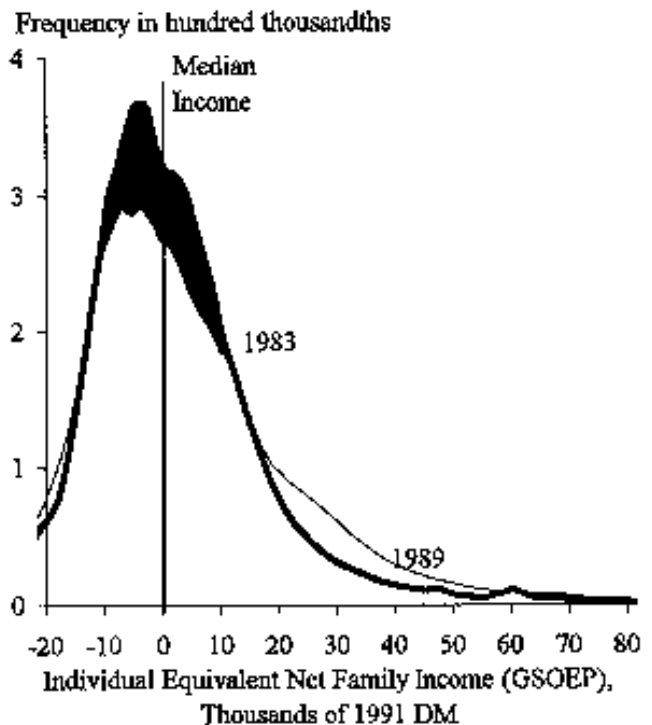
MEDIAN PRESERVING VIEW OF THE INCOME DISTRIBUTION IN THE UNITED STATES IN 1983 AND 1989



SOURCE: Authors' calculations based on PSID (1984 and 1990)

FIGURE 6

MEDIAN PRESERVING VIEW OF THE INCOME DISTRIBUTION OF GERMANY IN 1984 AND 1991



SOURCE: Authors' calculations based on GSOEP (1985 and 1992)

assistance, such as AFDC, General Assistance, and Supplementary Security Income, for their income support.

These three groups are selected for a number of reasons. First, in a society where work is the primary source of income, those persons living in families headed by a person who does not work are most likely to be vulnerable to economic risks. Hence, older people, who are predominately retired, and the families of younger heads who are not in the labor market are compared with the majority of younger families with one or two working adults. Second, during the period of strong economic growth that dominated the second half of the 1980s, public expenditures on social protection as a percentage of GDP fell in both the United States and Germany. To the extent that this decline reflects changes in the amount of social protection provided to younger non-working individuals and the elderly, the income distribution patterns among these groups and the remaining families should be different. Finally, while economic recovery is likely to increase the economic well-being of working individuals and their families, it is less clear how it will affect those families headed by older retired individuals or younger non-workers. Evaluating the experiences of each of these groups separately allows for the direct examination of the comparative changes in economic well-being over the last decade.

Table 2 reports the proportion of the population occupying each of these groups during the analysis years. As Table 2 indicates, the proportion of persons living in families headed by an older individual increased in both countries, moving above 20 percent of the total population in the United States and above 25 percent of the total population in Germany. This increase is consistent with demographic trends in both countries. Among the younger population, the proportion of persons living in families without a primary adult in the labor market decreased in both countries.

The results for the total population described in Figures 3 through 6 showed that in both countries the strong growth years contributed to inequality but did so in a way that disproportionately improved economic well-being. However, despite these disproportionate increases in economic well-being, a portion of the population was not helped by the recovery. To identify what segment(s) of the population did not benefit from economic growth, changes in income distribution among the three sub-groups are examined. Figures 7A–C show the graphs of the density functions for 1983 and 1989 by group for the United States. Figures 8A–C portray equivalent results for Germany. Combined, these figures show that the recovery did not affect all groups equally. Figure 7A portrays the income distribution for persons living in families with at least one younger primary

TABLE 2

PROPORTION OF POPULATION CLASSIFIED IN EACH GROUP BY YEAR

	UNITED STATES		GERMANY	
	1983	1989	1984	1991
	WEIGHTED PERCENTAGE	WEIGHTED PERCENTAGE	WEIGHTED PERCENTAGE	WEIGHTED PERCENTAGE
TOTAL POPULATION	100	100	100	100
PERSONS LIVING IN FAMILIES HEADED BY SOMEONE AGED 60 OR OLDER ^a	18.6	21.5	25.8	27.8
FAMILIES HEADED BY SOMEONE UNDER AGE 60 ^b				
PERSONS LIVING IN FAMILIES WITH AT LEAST ONE PRIMARY ADULT WORKING IN THE LABOR MARKET ^c	76.0	74.0	68.1	67.2
PERSONS LIVING IN FAMILIES WITH NO PRIMARY ADULTS WORKING IN THE LABOR MARKET ^d	5.4	4.5	6.2	5.0

^aFamilies in which the head or wife (partner) is aged 60 or older.

^bFamilies in which neither the head nor wife (partner) is aged 60 or older.

^cFamilies in which either the head or wife (partner) reported positive labor earnings.

^dFamilies in which neither the head nor wife (partner) reported positive labor earnings.

FIGURE 7A

THE INCOME DISTRIBUTION OF THE UNITED STATES IN 1983 AND 1989: CROSS-SECTIONAL DATA (YOUNGER WORKING POPULATION)

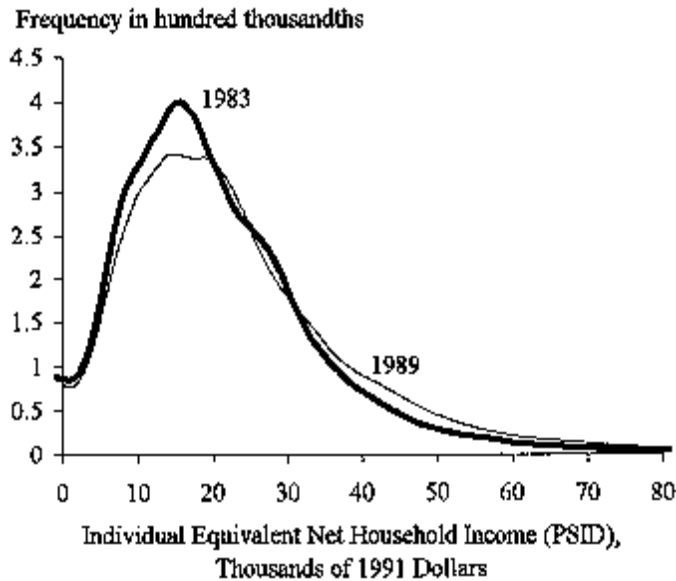


FIGURE 7C

THE INCOME DISTRIBUTION OF THE UNITED STATES IN 1983 AND 1989: CROSS-SECTIONAL DATA (YOUNGER NON-WORKING POPULATION)

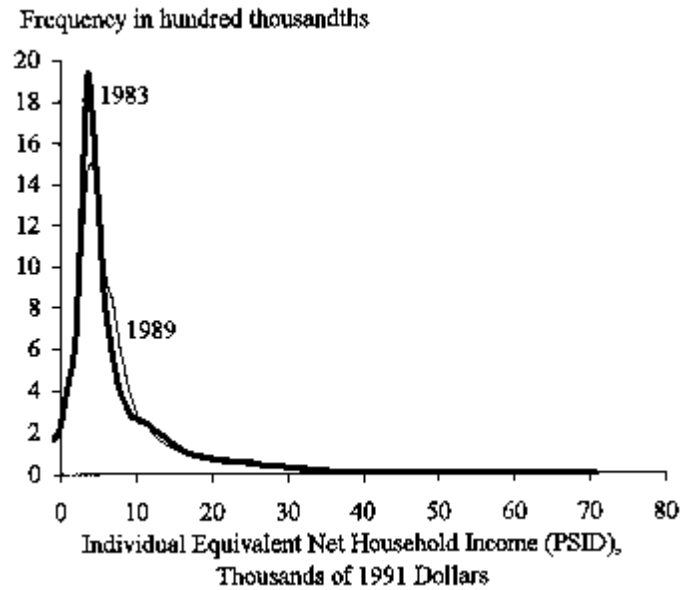
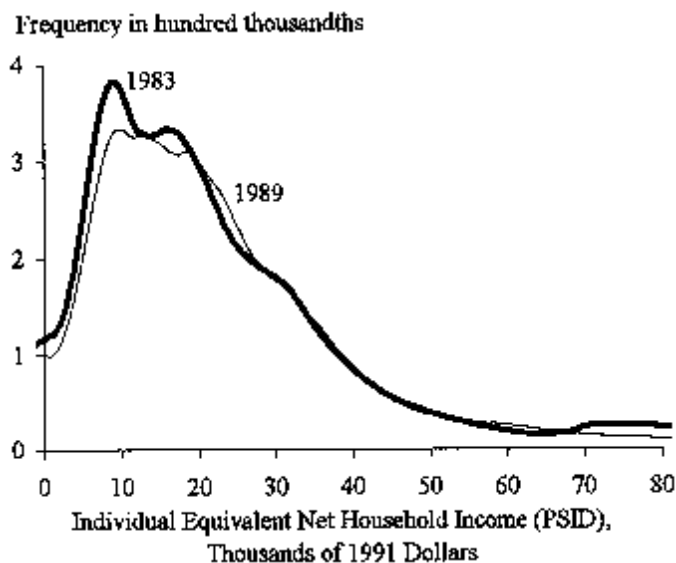


FIGURE 7B

THE INCOME DISTRIBUTION OF THE UNITED STATES IN 1983 AND 1989: CROSS-SECTIONAL DATA (POPULATION AGE 60+)



adult worker. As Figure 7A shows, economic growth during the 1980s significantly improved the economic well-being of younger working families.¹⁵ This pattern of change in economic fortunes also occurred in the older group. Although those over age 60 are frequently considered among those vulnerable to being left behind during periods of economic recovery and social policy retrenchment, almost the entire 1983 peak slid forward for this group, so that by 1989 the bulk of the older group was better off.

In contrast to the other two groups, persons living in families without a younger working head or partner were not among the beneficiaries of economic growth. Figure 7C demonstrates this point. The graphs of the 1983 and 1989 income distributions lie nearly on top of one another at the largest concentration of mass. Moreover, this concentration of mass is at the lower end of the distribution, under \$10,000.

Figures 8A–C examine changes in the income distribution by group for Germany. The patterns observed in the United States are also observed for Germany. Figure 8A

15. Analysis of younger families with one and two earners revealed similar patterns. Dual-earner families have higher average income than single-earner families, but relative to their starting positions both benefited equally from economic expansion.

FIGURE 8A

THE INCOME DISTRIBUTION OF GERMANY
IN 1984 AND 1991: CROSS-SECTIONAL DATA
(YOUNGER WORKING POPULATION)

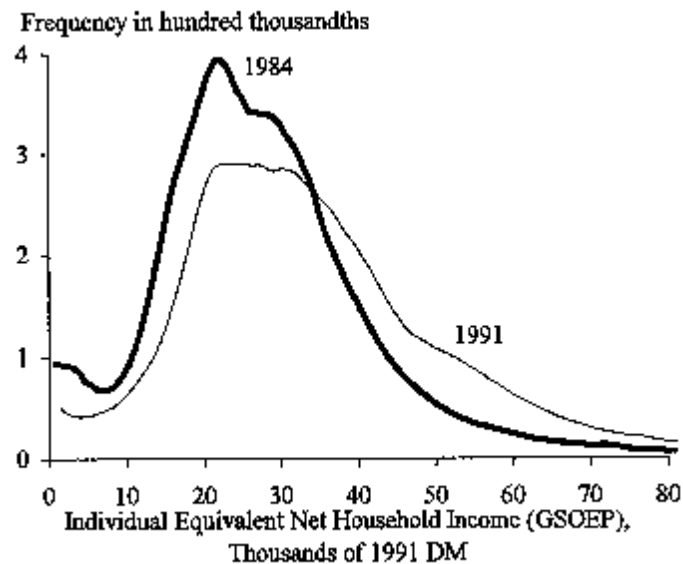


FIGURE 8C

THE INCOME DISTRIBUTION OF GERMANY
IN 1984 AND 1991: CROSS-SECTIONAL DATA
(YOUNGER NON-WORKING POPULATION)

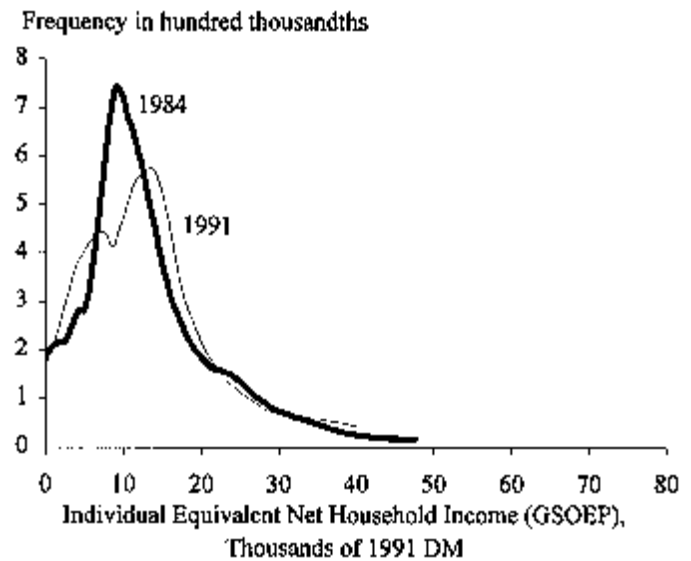
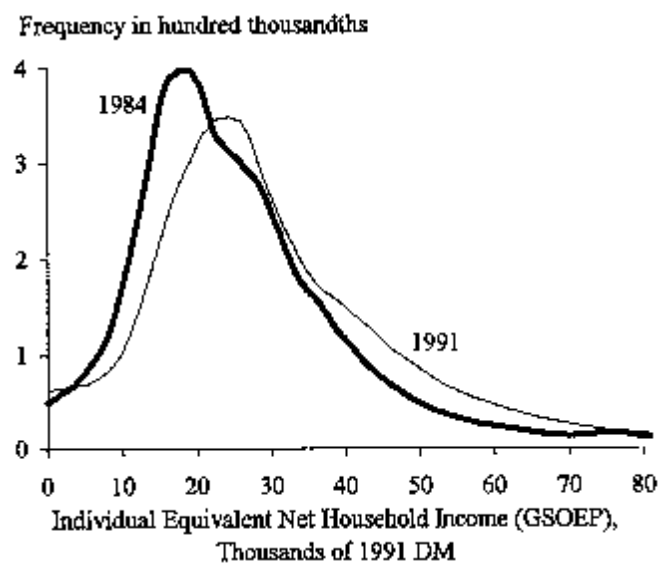


FIGURE 8B

THE INCOME DISTRIBUTION OF GERMANY
IN 1984 AND 1991: CROSS-SECTIONAL DATA
(POPULATION AGE 60+)



shows that for younger German families with at least one adult worker, the economic recovery substantially improved the fortunes of the majority of the population.¹⁶ As was the case for the total German population, a disproportionate amount of the decline in the middle of the distribution of persons living in younger working families fell to the right. Germans living in older families fared even better during the recovery, as their entire distribution of income shifted to the right.

Unlike Germans living in younger working families or in older families, the Germans living in younger non-working families did not benefit uniformly from the long period of economic recovery. In contrast to the other groups, as can be seen in Figure 8C, the substantial decline in the middle of the distribution spilled more equally into both tails of the distribution. Thus, by 1991, the shape of the income distribution for younger families without an adult worker was bimodal, with a significant peak on either side of the 1984 mode.

These findings underscore that the changing patterns of inequality associated with strong economic growth and social policy retrenchment have not been dominated by large declines in economic well-being but rather by significant

16. In Germany, both single- and dual-earner families gained from the expansion.

improvements in economic fortunes. However, they also point to the strong link between participating in the economy and benefiting from economic growth. Those individuals outside of the labor market did not share equally in the increases in economic well-being experienced by the other two groups. However, although persons living in younger non-working families at the end of the recovery were not uniformly better off than such persons at the beginning of the recovery period, in both countries the proportion of the population in this situation decreased as the economy expanded. The results from these three subgroups underscore the strong link between participating in the labor market and benefiting from economic growth.

VI. CONCLUSIONS

Consistent with previous research, this paper has shown that as the income distribution changed over the growth years of the 1980s, average income rose but so did inequality. However, as demonstrated, simple summary statistics cannot document where in the income distribution these changes took place and how these changes affected the economic well-being of different groups. Kernel density estimation provides a method by which to observe changes in the income distribution without assuming a particular functional form. Applying this technique, this paper has shown that while inequality increased in the United States between 1983 and 1989, almost all American families were economically better off in 1989 than in 1983 (the beginning of the recovery). Moreover, the largest share of the increase in income inequality over the decade of the 1980s was due to rapid but unequal income gains in the "middle" of the income distribution. On the whole, workers and older persons were better off at the end of the decade than at its beginning. The real losers in the 1980s were those persons living in younger families without an adult worker.

Comparing experiences in the United States with those in Germany reveals a similar story. For those currently and previously connected to the labor market, economic growth resulted in higher economic well-being; among those left behind, those living in younger families without an adult worker were predominant. Thus, despite the differences in social policy between the United States and Germany, some connection to the labor market was the key to benefiting from economic recovery in both countries. As in the United States, Germans without this connection did not equally benefit from economic growth.

While this paper only provides a descriptive analysis of the effects of economic growth on the income distributions in the United States and Germany, its findings suggest that even in countries committed to guaranteeing a minimum

level of well-being and spreading the benefits of economic growth to all citizens, the benefits of economic expansion are likely to be unevenly distributed. Future research in this area is required to begin to gauge the short- and long-term costs of this uneven distribution.

APPENDIX

CROSS-SECTIONAL PARAMETRIC MEASURES OF INEQUALITY

Formulas Used for Computation

The Gini coefficient:

$$\text{GINI} = \frac{1}{2n^2\mu} \sum_{i=1}^n \sum_{j=1}^n |y_i - y_j|,$$

in which y is individual income; n is the number of individuals; and μ is mean income.

90/10 percentile point measure:

$$(Y)_{p90} / (Y)_{p10}$$

where (Y) is equivalent household income assigned to all members of the household.

NOTE: The 90/50 and 50/10 measures are calculated analogously.

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Economic Factors, Monetary Policy, and Expected Returns on Stocks and Bonds

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This paper examines the impact of the stance of monetary policy on security returns. The two measures of the stance of monetary policy used, the federal funds rate and an index based on the change in the discount rate, contain significant information that can be used to forecast expected stock and bond portfolio returns. Specifically, we find that a restrictive (expansive) monetary policy stance decreases (increases) returns of large and small stock portfolios and, in some cases, corporate bond portfolios. The monetary policy stance measures have explanatory power in forecasting stock and bond returns, beyond the business conditions proxies.

A growing body of research has focused on forecasting stock and bond returns using economic and monetary factors. Fama and French (1988, 1989), Fama (1990), and Schwert (1990) focus on economic factors and find that three business conditions proxies, the dividend yield, default spread, and term spread, can explain significant variation in expected stock and/or bond returns. These studies generally find that the required returns that investors demand vary over the business cycle.

The majority of the research on monetary policy has focused on its impact in the real sector (see Romer and Romer 1989 and Bernanke and Blinder 1992). Less attention has been directed at the impact of monetary policy actions on stock and bond returns. Recently, Jensen, et al. (1996) used an index of the stance of monetary policy based on changes in the discount rate to show that expected stock returns are higher in expansive periods than in restrictive periods. Combining the previously used business cycle proxies with a measure of monetary policy, they find that the impact of the various business conditions proxies varies across monetary environments. Specifically, they find that the business conditions proxies have explanatory power only during restrictive periods.

In this study, we examine the impact of monetary policy on expected stock and bond returns and expand on previous work in several ways. First, we construct measures of the business conditions proxies in a slightly different way to test the robustness of the findings related to the predictability of stock returns. Second, we use two measures of monetary policy actions, the one developed by Jensen, et al. (1996) related to the directional change of the discount rate and one proxied by the federal funds rate, to determine whether there exists a direct monetary sector effect on stock and bond returns through these measures of monetary policy. Third, we examine a portfolio of small stocks and a portfolio of large stocks to determine whether the findings related to either the business conditions or monetary stringency have a differential impact given firm size. The motivation for this is based on the notion that smaller companies are more directly affected by changes in monetary policy due to their dependence on bank and private market financing.

We find, similar to earlier work on business conditions and expected returns, that the default spread, dividend yield, and the term spread are important in explaining expected returns on both large and small stock portfolios and on a portfolio of corporate bonds. We find that both measures of monetary policy actions have explanatory power for expected excess returns on the large stock portfolio and for the small stock portfolio in monthly returns. For the expected excess returns on corporate bonds, we find that the discount rate change measure of monetary policy stance has explanatory power. When we interact the discount rate change index with the business conditions proxies, we find that the monetary policy effect is direct and does not work through the business conditions proxies as suggested by Jensen, et al. (1996). We do find a larger monetary or business condition effect for smaller firms, consistent with a differential impact on these firms compared to large firms. Overall, these results suggest monetary policy actions can be used to forecast excess returns on stocks and bond portfolios.

I. RELATED RESEARCH

Business Conditions and Security Returns

The recent research on the relation between stock returns and business conditions have focused on three measures of the business environment: dividend yield, the default spread, and the term spread. Dividend yield, as a business conditions proxy, is perhaps the oldest of the measures believed to vary with expected stock returns (see Dow 1920). The intuition for this relation, provided by Fama (1990), is that stock prices are low relative to dividends when discount rates and expected returns are high, and vice versa, so $D(t)/V(t)$ varies with expected returns. Rozeff (1984), Shiller (1984), Campbell and Shiller (1987), Fama and French (1988, 1989), Fama (1990), and Jensen, et al. (1996) document that dividend yields forecast stock returns.

Evidence that the default spread is important in explaining stock and/or bond returns is more recent. Chen, Roll, and Ross (1986) argue that the spread of lower- to higher-grade bonds is a proxy for business conditions. They argue that when business conditions are poor, spreads are likely to be high, and when business conditions are strong, spreads are likely to be low. Studies by Fama and French (1989), Fama (1990), and to a lesser degree Jensen, et al. (1996), find that the default spread captures variations in expected returns in response to business conditions.

The third measure of business conditions that has been used in previous studies is the term spread. The motivation for this is that the term spread is shown to decrease near

peaks of economic activity and increase near economic troughs. Consistent with this motivation, Campbell (1987), Fama and French (1989), Fama (1990), Schwert (1990), Shiller (1984), Campbell and Shiller (1987), and Jensen, et al. (1996) find that the term spread also explains similar variations in expected stock returns.

Monetary Policy and Security Returns

It has long been contended that monetary policy affects not only economic activity, but also security returns. An early examination of the link between stock returns and monetary policy by Rozeff (1984) finds a relation between stock returns and contemporaneous monetary policy developments. Additional studies by Shiller (1984), Campbell and Shiller (1987), Geske and Roll (1983), and Kaul (1987) present evidence linking the monetary sector to stock returns.

More recently, Jensen and Johnson (1995) find that stock returns are related to changes in the Federal Reserve discount rate. In Jensen, et al. (1996), this measure of monetary policy is used to show that business conditions proxies used in previous studies (as discussed above) vary dramatically across monetary environments. Their motivation for using the discount rate as a proxy for the stance of monetary policy follows from the view that the discount rate is routinely regarded as a signal of monetary and possibly economic developments. Their argument is based on Waud's (1970) suggestion that discount rate changes affect market participants' expectations about monetary policy because (1) rate changes are made only at substantial intervals, (2) they represent a somewhat discontinuous instrument of monetary policy, and (3) they are established by a public body perceived as being competent in judging the economy's cash and credit needs. Using discount rate change series as their measure of expansive and restrictive policies, they are able to show that the behavior of the business conditions proxies and their influence on expected returns is significantly affected by the monetary environment.

We reexamine the impact of monetary policy based on the measure developed by Jensen, et al. (1996) with slightly different proxies for business conditions. We also use the federal funds rate, based on evidence by Bernanke and Blinder (1992) and Laurent (1988) that the federal funds rate is a good indicator of monetary policy actions. To examine whether business conditions and monetary policy have a differential impact on small versus large stocks, we examine expected returns on a portfolio of the S&P 500 firms, a portfolio of small stocks (approximately the fifth quintile of firms on the New York Stock Exchange), and a portfolio of Aaa and Aa rated bonds. This allows us to test for

a differential impact of both business conditions and monetary policy on large versus small firm returns and on bond returns.

II. DATA

Sample Period

We examine stock and bond returns over the period August 1954 through December 1992. This follows closely the sample period chosen by Jensen, et al. (1996) and the first availability of the federal funds rates. Even though February 1954 reflects the first change in stance through the discount rate since the Federal Reserve/Treasury accord of 1951, we start our sample from August 1954 to match the federal funds rate data. This permits us to compare the information contained in each measure.

Following the Jensen, et al. (1996) approach in constructing the discount rate series, we find this 39-year period includes a total of 99 discount rate changes, 49 increases and 50 decreases. They define a rate change series as a period of time over which discount rate changes are in only one direction, either increasing or decreasing. This results in 23 rate change series, 12 decreasing and 11 increasing. Using this framework, we accept their notion that a series reflects a period in which the Fed is operating under the same monetary policy; the next series occurs when a rate change in the opposite direction is announced. The months in which rates are announced are eliminated from the sample. This results in 439 monthly observations, 239 months following discount rate increases and 200 following discount rate decreases.

In the quarterly sample, we have 131 observations. This is 11 quarters fewer than that of Jensen, et al. (1996) because

TABLE 1

FEDERAL RESERVE DISCOUNT RATE CHANGE SERIES: FEBRUARY 1954 THROUGH DECEMBER 1992

SERIES	INCREASING (I) OR DECREASING (D)	FIRST RATE CHANGE	NUMBER OF RATE CHANGES	MONTHLY OBSERVATIONS
1	D	02/05/54	2	13
2	I	04/14/55	5	30
3	D	11/15/57	4	8
4	I	08/15/58	5	21
5	D	06/30/60	2	36
6	I	07/17/63	3	44
7	D	04/07/67	1	6
8	I	11/20/67	3	8
9	D	08/16/68	1	3
10	I	12/19/68	2	22
11	D	11/11/70	5	7
12	I	07/16/71	1	3
13	D	11/11/71	2	13
14	I	01/15/73	8	22
15	D	12/09/74	7	31
16	I	08/30/77	14	32
17	D	05/29/80	3	3
18	I	09/26/80	4	13
19	D	11/02/81	9	28
20	I	04/09/84	1	6
21	D	11/23/84	7	33
22	I	09/04/87	3	38
23	D	12/18/90	7	24

SOURCE: Extracted from Jensen, et al. (1996).

of the creation of quarters around rate changes. They drop months when the number of months in a rate change series is not divisible by 3. We use the traditional calendar quarters and eliminate the quarters in which a rate change occurred. This analysis places the monthly and quarterly data into one of two subsamples: observations that occur during increasing rate series and observations that occur during decreasing rate series. Table 1 provides the number of months and quarters in each rate change series.

Return and Macroeconomic Variables

The return and explanatory variables follow those used in previous studies, particularly Fama (1990) and Jensen, et al. (1996).

Return Variables

Large stock returns (LS): Monthly stock returns for the large stock portfolio are collected from Ibbotson and Associates for the sample period February 1954 through December 1992. The data comprise the total returns, including dividends, for the S&P 500 after March 1957 and for the S&P 90 stocks before 1957. These represent a portfolio of the largest market value companies in the U.S. The portfolio returns are value-weighted. To obtain a measure of excess returns, we subtract the contemporaneous monthly return on T-bills.

Small stock returns (SS): These are the monthly returns on the Ibbotson small stock portfolio for the same sample period. For the period February 1954 to December 1981, this portfolio was the Dimensional Fund Advisors (DFA) Small Company 9/10 (ninth and tenth) Fund. The fund is a market-value-weighted index of the ninth and tenth deciles of the New York Stock Exchange (NYSE), plus stocks listed on the American Stock Exchange (AMEX) and over-the-counter (OTC) with capitalization that is the same as or less than the upper bound of the NYSE ninth decile.

The weight of each stock within the fund is proportionate to its market capitalization; therefore, stocks with a higher market capitalization value will be weighted more than stocks with a lower market capitalization value. Since the lower bound of the tenth decile is near zero, stocks are not purchased if they are smaller than \$10 million in market capitalization (although they are held if they fall below that level). A company's stock is not purchased if it is in bankruptcy; however, a stock already held is retained if the company becomes bankrupt. Stocks remain in the portfolio if they rise into the eighth NYSE decile, but they are sold when they rise into the seventh NYSE decile or higher. The returns for the DFA Small Company 9/10 Fund repre-

sent after-transactions-cost returns while the returns on other asset classes and for the pre-1982 small company stocks are before-transactions-cost returns.

For the period after 1982, the small stock portfolio is represented by the historical series developed by Banz (1981). This equals the fifth quintile of the NYSE, based on market value. Every five years the portfolio is rebalanced and the new portfolio includes the new fifth quintile of the NYSE. Excess returns are obtained by subtracting the return on the contemporaneous T-bill.

Corporate bond returns (CB): The corporate bond total returns are represented by the Salomon Brothers Long-Term High-Grade Corporate Bond Index. According to Ibbotson Associates, the index includes nearly all Aaa- and Aa-rated bonds. Capital appreciation returns were calculated from yields assuming a 20-year maturity, a bond price equal to par, and a coupon equal to the beginning-of-period yield. The monthly income return was assumed to be one-twelfth the coupon. The monthly return on the T-bill is subtracted to obtain excess returns.

Explanatory Variables

Dividend yield (D/P): To obtain the dividend yield for the large stock portfolio, we use the income return calculated by Ibbotson Associates. Following Fama and French (1989), we use annual income returns as the independent variable.

Term spread (TERM): To calculate the term spread, we use the long-term government bond return from Ibbotson Associates. For the 1954 to 1976 period, this involved using approximately 20 bonds with reasonably current coupons. For the 1977–1992 period, the return was calculated as the change in the price plus the coupon payments. To develop a measure of TERM, we subtract the contemporaneous T-bill return from the long-term government bond return. This measure differs from Fama (1990) and Jensen, et al. (1996) in that they measure the difference between the 10-year and 1-year T-bond returns.

Default spread (DEF): The default spread is measured as the difference between the return on the corporate bond portfolio and the T-bond portfolio. Our measure is obtained by subtracting the 20-year T-bond portfolio return (approximately) from the return of a portfolio containing Aaa- and Aa-rated corporate bonds. This measure is closest to the Jensen, et al., measure of the Baa corporate bond minus the 10-year T-bond. Fama (1990) and Fama and French (1989) use the difference between a portfolio of all corporate bonds and the yield on the Aaa corporate portfolio. Schwert (1990) uses the difference in yield between Baa and Aa-rated corporate bonds.

Discount rate changes (DIR): This is a binary variable taking on the value of one if the previous discount rate change was an increase and zero if the previous change was a decrease.

Federal funds rate (FFRATE): This annualized rate equals the monthly and quarterly averages of daily federal funds rates collected from the Federal Reserve Bank of St. Louis (FRED) data series.

To obtain security returns for the analysis involving quarterly holding periods, we cumulate monthly observations. Following previous studies, we use excess returns of large stocks (LS), small stocks (SS), and corporate bonds (CB) as dependent variables. Consistent with earlier approaches, we focus on expected returns. In performing the statistical analysis, we lag the independent variables D/P, TERM, DEF, and FFRATE by one period relative to the excess returns variables.

III. EMPIRICAL RESULTS

Variable Means across Monetary Environments

Table 2 presents the means of the variables used in the analysis across the sample period and during the expansive and restrictive monetary periods, based on the discount rate index constructed according to the Jensen, et al. (1996) approach. The excess return variables for our large stock portfolio, which is based on the S&P 500, are similar in

magnitude to those reported for the value-weighted CRSP index in Jensen, et al. The excess returns for our small stock portfolio are slightly higher than those reported for the equally weighted CRSP index in Jensen, et al. The excess returns for our portfolio of high-grade corporate bonds are consistent with the findings of Jensen, et al., and Rozeff (1984), who find that stock returns vary across the monetary policy environment.

The results on annual dividend yield are slightly lower than those reported for the CRSP index by Jensen, et al., and by Fama and French (1990). The difference across monetary policy environments is similar to that reported in Jensen, et al. Our measure of TERM differs substantially, both in construction and in results, from other studies. We use the difference between the long-term 20-year T-bond and the T-bill rates; Jensen, et al., uses the difference between the 10-year and 1-year Treasury yields, and Fama (1990), Fama and French (1989), and Schwert (1990) use the difference between corporate bond yields and the T-bill. Compared to the results in Jensen, et al., the mean of our variable is lower, and our measure shows much greater variation across different monetary regimes. We prefer it because it reflects the spread between two of the more liquid Treasury issues and does not contain any potential for a default spread, as do the measures using corporate series.

Our measure of the default spread (DEF) uses the difference between the return on the portfolio of Aaa- and Aa-rated corporate bonds and the return on long-term T-bonds. Earlier studies use the difference between high- and low-grade corporate bonds (Fama 1990 and Schwert 1990).

TABLE 2

MEANS OF OBSERVATIONS OF BUSINESS CONDITIONS PROXIES AND SECURITY RETURNS: AUGUST 1954 THROUGH DECEMBER 1992

VARIABLE	FULL SAMPLE (n = 439)	EXPANSIVE PERIODS (n = 200)	RESTRICTIVE PERIODS (n = 239)	t TEST
SECURITYRETURNS (MONTHLY):				
Large stock excess returns (LS)	0.523	1.299	-0.125	3.49**
Small stock excess returns (SS)	0.885	1.932	0.008	3.42**
High-grade bond excess returns (CB)	0.088	0.418	-0.187	2.70**
BUSINESS CONDITIONS PROXIES (ANNUALIZED):				
Term spread (TERM)	0.072	6.067	-4.884	12.84**
Dividend yield (D/P)	4.065	4.153	3.991	1.89
Default spread (DEF)	0.737	1.325	0.246	2.58**
FEDERALFUNDS RATE (ANNUALIZED):	6.298	5.490	6.975	4.43**

** Statistically significant at the 0.01 level

Our measure is closer to that used in Jensen, et al. (1996), viz, the Baa-rated corporate bond minus the 10-year T-bond yield. Compared to the measure used by Jensen, et al., our measure of the default spread, DEF, has a smaller mean, and it exhibits greater variability over different monetary regimes. This is consistent with the interpretation of Jensen, et al., that there is an increasing concern about a firm's ability to service its debt during expansive periods. This is also consistent with higher risk premiums during economic downturns.

Our results for the second measure of monetary policy actions, the federal funds rate, indicate that the level of the federal funds rate is consistent with the direction of monetary policy indicated by the discount rate change measure. The correlation between the federal funds rate and the discount rate index is 0.22. Thus, they both contain unique information that may affect expected returns.

Business Conditions Proxies and Expected Returns

In Table 3, we provide regressions of business conditions on the expected returns on stocks and bonds. The results presented here are similar to earlier studies by Fama and French (1989) and Jensen, et al. (1996). We find that our measure of the term spread (TERM) has a positive coefficient and is significant in explaining returns of large stocks, small stocks, and corporate bonds for both monthly and quarterly horizons. This finding is consistent with Fama and French (1989), Fama (1990), and Jensen, et al. (1996). The dividend yield (D/P) has explanatory power for large and small stock returns but not for corporate bond returns in the monthly returns. For the quarterly horizon, D/P loses significance for large and small stocks and corporate bonds. These findings differ from those of Fama and French (1989) and the monthly returns of Jensen, et al. (1996), who find that D/P has explanatory power for corporate bond returns. For quarterly returns, we find that D/P does not have explanatory power for either stocks or bonds.

We find the default spread (DEF) has explanatory power for monthly returns of large and small stocks but not for corporate bonds. Over the quarterly return horizon, we find that DEF has explanatory power in forecasting quarterly corporate bond returns as well as large- and small-stock portfolios returns. Jensen, et al. (1996) find that the default spread is important only in explaining equally weighted stock portfolio returns. Overall, we find that the business conditions proxies have explanatory power for explaining stock and bond returns on both monthly and quarterly return horizons. Our results for the dividend yield (D/P) are not as strong as earlier studies but may reflect differences in the computation of this variable.

Monetary Sector and Security Returns

In Table 4, we add the proxies for monetary policy stance, the federal funds rate and the discount rate change series. The coefficients for the federal funds rate (FFRATE) in the monthly regressions are negative and statistically significant for the large and small stock regressions but not significant in the bond return regressions. The coefficient for DIR (value of one during restrictive periods) is negative and statistically significant at the 0.05 level for all the monthly regressions.

For the quarterly regressions in Table 4, the results are quite different. The federal funds rate (FFRATE) is important only in predicting large stock returns. The discount rate change (DIR) has explanatory power only for corporate bond returns. DIR has explanatory power for large stocks returns when FFRATE is not included.

The regressions indicate that both the changes in the federal funds rate (FFRATE) and the discount rate series (DIR) have explanatory power for predicting excess stock returns, but only the DIR measure has explanatory power for predicting excess bond returns. These results indicate that the returns on all portfolios are higher during expansive monetary periods than during restrictive periods.

We also find that the business conditions proxies have explanatory power for stock and bond returns. The addition of the proxies for monetary restrictiveness alters, to a slight degree, the explanatory power of the business conditions proxies for stock and bond portfolio returns. In particular, the coefficient and explanatory power of D/P, the dividend yield, is consistently smaller for large stock, small stock, and corporate bond portfolios. The coefficients on TERM remain statistically significant for most stock regressions. These results differ from those of Jensen, et al. (1996), who find that the introduction of the monetary policy variable causes their measure for the term spread to lose explanatory power for all stock regressions, although it is still significant in the monthly and quarterly bond portfolio regressions. The default spread (DEF) loses explanatory power, although it is still significant at the 0.10 level for the large and small stock portfolios in the monthly regressions. For the quarterly return horizons, DEF continues to be significant at the 0.05 level for the stock regressions. Thus, the introduction of the two proxies only slightly alters the results related to the business conditions proxies. This suggests the potential for a direct monetary policy effect on expected stock and bond returns.

In Table 5, we present evidence related to the stability of the slope parameters across monetary policy environments. To do this, we interact DIR with the business conditions proxies TERM, D/P, and DEF, and this is done with and without the federal funds rate (FFRATE) included. In

TABLE 3

RESULTS OF REGRESSIONS OF BUSINESS CONDITIONS ON THE EXPECTED RETURNS OF STOCKS AND BONDS:
FEBRUARY 1954 THROUGH DECEMBER 1992

MONTHLY RETURNS						
DEPENDENT VARIABLE	CONSTANT	TERM	D/P	DEF	Adj. R^2	F TEST
(1) LARGE STOCK PORTFOLIO	-0.011 (-1.197)	0.269 (3.112)**	0.404 (1.809)	0.404 (2.256)*	0.02	4.62 [0.01]
(2) SMALL STOCK PORTFOLIO	-0.015 (-1.172)	0.409 (3.446)**	0.582 (1.899)	0.549 (2.232)*	0.03	5.35 [0.01]
(3) BOND PORTFOLIO	0.003 (0.660)	0.116 (2.441)*	-0.063 (-0.513)	0.086 (0.881)	0.01	2.10 [0.10]
(4) LARGE STOCK PORTFOLIO	-0.011 (-1.155)	0.184 (2.354)*	0.402 (1.790)		0.02	4.35 [0.01]
(5) SMALL STOCK PORTFOLIO	-0.014 (-1.131)	0.294 (2.735)**	0.579 (1.879)		0.02	5.48 [0.01]
(6) BOND PORTFOLIO	0.003 (0.674)	0.097 (2.286)*	-0.063 (-0.518)		0.01	2.75 [0.06]
(7) LARGE STOCK PORTFOLIO	0.005 (2.626)**	0.268 (3.092)**		0.403 (2.242)*	0.02	5.27 [0.01]
(8) SMALL STOCK PORTFOLIO	0.009 (3.140)**	0.408 (3.423)**		0.547 (2.217)*	0.02	6.18 [0.01]
(9) BOND PORTFOLIO	0.001 (0.732)	0.116 (2.446)*		0.087 (0.884)	0.01	3.01 [0.05]

QUARTERLY RETURNS						
DEPENDENT VARIABLE	CONSTANT	TERM	D/P	DEF	Adj. R^2	F TEST
(1) LARGE STOCK PORTFOLIO	-0.033 (-1.042)	0.558 (3.507)**	1.114 (1.444)	1.122 (2.589)**	0.10	5.66 [0.00]
(2) SMALL STOCK PORTFOLIO	-0.037 (-0.767)	0.875 (3.676)**	1.457 (1.262)	1.669 (2.619)**	0.10	5.86 [0.00]
(3) BOND PORTFOLIO	0.010 (0.610)	0.240 (2.862)**	-0.236 (-0.579)	0.485 (2.118)*	0.05	3.26 [0.02]
(4) LARGE STOCK PORTFOLIO	-0.032 (-0.989)	0.411 (2.709)**	1.128 (1.432)		0.06	4.92 [0.01]
(5) SMALL STOCK PORTFOLIO	-0.035 (-0.719)	0.654 (2.874)**	1.478 (1.253)		0.06	5.13 [0.01]
(6) BOND PORTFOLIO	0.011 (0.627)	0.177 (2.227)*	-0.230 (-0.557)		0.02	2.57 [0.08]
(7) LARGE STOCK PORTFOLIO	0.012 (1.726)	0.570 (3.575)**		1.126 (2.588)**	0.09	7.38 [0.00]
(8) SMALL STOCK PORTFOLIO	0.022 (2.183)	0.892 (3.742)**		1.705 (2.622)**	0.10	7.96 [0.00]
(9) BOND PORTFOLIO	0.001 (0.209)	0.238 (2.842)**		0.484 (2.119)*	0.05	4.74 [0.01]

* Statistically significant at the 0.05 level

** Statistically significant at the 0.01 level

NOTES: t statistics in parentheses; p values in brackets.

TABLE 4

RESULTS OF REGRESSIONS OF BUSINESS CONDITIONS AND MONETARY POLICY PROXIES
ON THE EXPECTED RETURNS OF STOCKS AND BONDS: AUGUST 1954 THROUGH DECEMBER 1992

DEPENDENT VARIABLE	MONTHLY RETURNS							F TEST
	CONSTANT	TERM	D/P	DEF	FFRATE	DIR	ADJ. R ²	
(1) LARGE STOCK PORTFOLIO	-0.008 (-0.840)	0.242 (2.806)**	0.616 (2.577)**	0.383 (2.149)*	-0.193 (-3.210)**		0.04	5.93 [0.00]
(2) SMALL STOCK PORTFOLIO	-0.012 (-0.947)	0.383 (3.219)**	0.854 (2.585)**	0.526 (2.137)*	-0.222 (-2.662)**		0.04	5.78 [0.00]
(3) BOND PORTFOLIO	0.004 (0.678)	0.113 (2.364)*	-0.039 (-0.297)	0.082 (0.829)	-0.017 (-0.520)		0.01	1.62 [0.17]
(4) LARGE STOCK PORTFOLIO	-0.001 (-0.074)	0.216 (2.456)*	0.294 (1.301)	0.358 (1.991)*		-0.011 (-2.749)**	0.04	5.22 [0.00]
(5) SMALL STOCK PORTFOLIO	-0.003 (-0.202)	0.346 (2.853)**	0.476 (1.529)	0.488 (1.969)*		-0.015 (-2.587)**	0.04	5.68 [0.00]
(6) BOND PORTFOLIO	0.007 (1.357)	0.092 (1.888)	-0.090 (-0.724)	0.056 (0.570)		-0.005 (-2.307)*	0.02	2.90 [0.02]
(7) LARGE STOCK PORTFOLIO	-0.001 (-0.151)	0.206 (2.356)*	0.529 (2.190)*	0.341 (1.908)	-0.163 (-2.634)**	-0.009 (-2.054)*	0.05	5.62 [0.00]
(8) SMALL STOCK PORTFOLIO	-0.004 (-0.264)	0.335 (2.770)**	0.737 (2.206)*	0.469 (1.900)	-0.180 (-2.109)*	-0.011 (-2.015)*	0.05	5.47 [0.00]
(9) BOND PORTFOLIO	0.007 (1.355)	0.092 (1.886)	-0.092 (-0.684)	0.057 (0.570)	0.001 (0.032)	-0.005 (-2.244)*	0.01	2.31 [0.04]

DEPENDENT VARIABLE	QUARTERLY RETURNS							F TEST
	CONSTANT	TERM	D/P	DEF	FFRATE	DIR	ADJ. R ²	
(1) LARGE STOCK PORTFOLIO	-0.007 (-0.211)	0.481 (3.252)**	1.277 (1.595)	1.001 (2.411)*	-0.527 (-2.582)**		0.12	5.62 [0.00]
(2) SMALL STOCK PORTFOLIO	-0.015 (-0.307)	0.826 (3.609)**	1.754 (1.416)	1.613 (2.510)*	-0.527 (-1.670)		0.11	5.21 [0.00]
(3) BOND PORTFOLIO	0.017 (0.923)	0.161 (1.839)	-0.179 (-0.379)	0.357 (1.463)	-0.180 (-1.498)		0.03	1.87 [0.12]
(4) LARGE STOCK PORTFOLIO	0.010 (0.292)	0.355 (2.145)*	0.464 (0.610)	0.971 (2.279)*		-0.029 (-1.960)*	0.11	4.81 [0.00]
(5) SMALL STOCK PORTFOLIO	-0.005 (-0.099)	0.745 (2.915)**	0.971 (0.828)	1.642 (2.500)*		-0.020 (-0.864)	0.10	4.63 [0.00]
(6) BOND PORTFOLIO	0.032 (1.693)	0.052 (0.548)	-0.500 (-1.155)	0.261 (1.075)		-0.023 (-2.782)**	0.07	3.31 [0.01]
(7) LARGE STOCK PORTFOLIO	0.010 (0.298)	0.368 (2.257)*	1.130 (1.412)	0.865 (2.053)*	-0.477 (-2.324)*	-0.024 (-1.620)	0.14	5.07 [0.00]
(8) SMALL STOCK PORTFOLIO	-0.005 (-0.099)	0.758 (2.981)**	1.666 (1.333)	1.531 (2.329)*	-0.497 (-1.552)	-0.014 (-0.624)	0.11	4.23 [0.00]
(9) BOND PORTFOLIO	0.032 (1.695)	0.055 (0.585)	-0.314 (-0.677)	0.231 (0.948)	-0.133 (-1.123)	-0.022 (-2.583)**	0.07	2.91 [0.02]

* Statistically significant at the 0.05 level

** Statistically significant at the 0.01 level

NOTES: *t* statistics in parentheses; *p* values in brackets.

TABLE 5
RESULTS ON THE STABILITY OF THE SLOPE PARAMETERS ACROSS MONETARY POLICY ENVIRONMENTS

DEPENDENT VARIABLE	MONTHLY RETURNS											F TEST
	CONSTANT	TERM	D/P	DEF	FRRATE	DIR	TERM*DIR	D/P*DIR	DEF*DIR	Adj. R ²		
(1) LARGE STOCK PORTFOLIO	0.016 (1.134)	0.106 (0.844)	-0.106 (-0.313)	0.438 (1.989)*		-0.044 (-2.314)*	0.286 (1.616)	0.806 (1.767)	-0.299 (-0.929)	0.05	4.26 [0.00]	
(2) SMALL STOCK PORTFOLIO	0.012 (0.588)	0.297 (1.715)	0.126 (0.268)	0.810 (2.164)*		-0.042 (-1.593)	0.163 (0.663)	0.677 (1.073)	-0.557 (-1.113)	0.04	3.83 [0.00]	
(3) BOND PORTFOLIO	0.003 (0.335)	0.074 (1.055)	0.025 (0.132)	0.088 (0.585)		0.003 (0.267)	0.030 (0.312)	-0.199 (-0.782)	-0.067 (-0.332)	0.01	1.79 [0.09]	
(4) LARGE STOCK PORTFOLIO	0.014 (0.998)	0.123 (0.984)	0.136 (0.385)	0.558 (2.075)*	-0.149 (-2.392)*	-0.039 (-2.037)*	0.231 (1.301)	0.740 (1.629)	-0.364 (-1.012)	0.06	4.48 [0.00]	
(5) SMALL STOCK PORTFOLIO	0.009 (0.471)	0.317 (1.833)	0.409 (0.835)	0.834 (2.234)*	-0.174 (-2.013)*	-0.036 (-1.357)	0.098 (0.399)	0.600 (0.951)	-0.633 (-1.266)	0.05	3.88 [0.00]	
(6) BOND PORTFOLIO	0.003 (0.335)	0.073 (1.051)	0.024 (0.121)	0.088 (0.583)	0.001 (0.015)	0.003 (0.263)	0.031 (0.311)	-0.198 (-0.779)	-0.066 (-0.330)	0.01	1.57 [0.13]	

DEPENDENT VARIABLE	QUARTERLY RETURNS											F TEST
	CONSTANT	TERM	D/P	DEF	FRRATE	DIR	TERM*DIR	D/P*DIR	DEF*DIR	Adj. R ²		
(1) LARGE STOCK PORTFOLIO	0.062 (1.293)	0.324 (1.534)	-0.748 (-0.654)	0.747 (1.296)		-0.126 (-1.978)*	0.209 (0.583)	2.398 (1.548)	0.609 (0.708)	0.11	3.21 [0.00]	
(2) SMALL STOCK PORTFOLIO	0.045 (0.608)	1.020 (3.121)**	-0.424 (-0.239)	2.368 (2.655)**		-0.103 (-1.094)	-0.588 (-1.059)	2.154 (0.898)	-1.459 (-1.095)	0.10	2.97 [0.00]	
(3) BOND PORTFOLIO	0.003 (0.125)	-0.125 (-1.053)	0.307 (0.477)	-0.099 (-0.306)		0.023 (0.663)	0.412 (2.041)*	-1.205 (-1.382)	0.698 (1.441)	0.09	2.83 [0.01]	
(4) LARGE STOCK PORTFOLIO	0.057 (1.210)	0.395 (1.870)	-0.065 (-0.055)	0.782 (1.374)	-0.440 (-2.057)*	-0.110 (-1.748)	0.029 (0.080)	2.144 (1.398)	0.319 (0.370)	0.13	3.41 [0.00]	
(5) SMALL STOCK PORTFOLIO	0.038 (0.524)	1.120 (3.414)**	0.535 (0.293)	2.417 (2.735)**	-0.617 (-1.859)	-0.081 (-0.834)	-0.840 (-1.484)	1.798 (0.755)	-1.866 (-1.396)	0.11	3.08 [0.00]	
(6) BOND PORTFOLIO	0.002 (0.090)	-0.111 (-0.916)	0.447 (0.664)	-0.092 (-0.283)	-0.089 (-0.735)	0.027 (0.743)	0.375 (1.801)	-1.257 (-1.434)	0.638 (1.298)	0.09	2.53 [0.01]	

* Statistically significant at the 0.05 level

** Statistically significant at the 0.01 level

NOTES: *t* statistics in parentheses; *p* values in brackets.

the monthly regressions for the large stock portfolio, the coefficient on TERM*DIR is positive but not statistically significant at traditional levels. However, the addition causes the statistical significance of TERM to be reduced. DEF continues to be significant, but DEF*DIR lacks explanatory power in explaining large and small stock returns and corporate bond returns. The default spread DEF continues to have explanatory power for large and small stock returns, but not corporate bonds, while the interaction of DEF*DIR is insignificant in forecasting any of the return series. DIR, the proxy for a restrictive monetary environment, continues to have explanatory power in many of the monthly regressions, particularly for the large stock portfolio. For both small stocks and corporate bonds, we find that DIR is not significant whether FFRATE is included or not.

In the quarterly regressions, we find that only one of the interaction terms (TERM*DIR) has explanatory power in forecasting bond return series. The coefficient on DIR is significant at the 0.05 level in forecasting returns on the large stock portfolio. For the small stock portfolio, we find that both the term spread (TERM) and the default spread (DEF) are significant in explaining quarterly returns.

Overall, from these results, we conclude that monetary policy has explanatory power in forecasting large and small stock portfolio returns, as well as returns on high grade corporate bonds. This is supported by both measures of the stance of monetary policy: the index of change in the discount rate and the federal funds rate. Tests of the stability of the slope parameters across the monetary regimes indicate that the slopes do not change in the restrictive monetary policy environments and that monetary policy continues to forecast large stock returns in most regressions. These results differ from those of Jensen, et al. (1996) in which they cannot determine that monetary policy explains unique variations in security returns beyond that explained by the business conditions proxies. We find that monetary policy has unique explanatory power in forecasting large and small stock monthly portfolio returns, even after controlling for its potential effect through the business conditions proxies. We find that the discount rate change proxy is important in forecasting excess bond and stock returns. After controlling for interaction of this measure and the business conditions proxies, we find it only predicts large stock returns.

IV. SUMMARY AND CONCLUSIONS

We present evidence that the stance of monetary policy has explanatory power for large stocks, small stocks, and corporate bonds. These results confirm earlier findings by Jensen, et al. (1996). Using two measures of monetary policy actions, the federal funds rate and an index based on the change in the discount rate, we show that monetary condi-

tions have explanatory power beyond business conditions proxies. In particular, we find that a restrictive monetary policy stance lowers monthly returns of large and small stock portfolios, and in some cases, corporate bonds.

These results differ from those of Jensen, et al. (1996) in that our business conditions proxies play substantially different roles in explaining variations in expected stock and bond returns, depending on monetary stringency. We do not confirm their findings that only during restrictive monetary policy environments do the business conditions proxies contain significant explanatory power for stocks and bonds. The difference in the findings can possibly be explained by differences in the definitions of the business conditions proxies or by differences in the stock and bond portfolios we examine. If this is the case, it suggests that earlier findings may not be robust to slightly different ways of measuring the business conditions proxies, or they may be sensitive to the particular stock and bond portfolios considered.

Overall, these results indicate that monetary policy actions contain significant information that may be used to forecast expected stock and bond portfolio returns. In addition, we find that information is reflected in the federal funds rate, beyond that indicated by the discount rate changes. This information can be used to forecast stock and bond returns beyond that contained in proxies for the business cycle.

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