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ABSTRACT

The real business cycle literature has largely ignored the empirical question of what role technology shocks actually play in business cycles. The observed procyclicality of total factor productivity (TFP) does not prove that technology shocks are important to business cycles, since demand shocks could generate procyclical TFP due to increasing returns or other reasons. I address the role of technology by investigating the dynamic interactions of inputs, TFP and two observable indicators of technology shocks: R+D spending and patent applications. Using annual panel data on 19 US manufacturing industries from 1959 -1991, I find that favorable R+D or patent shocks tend to increase inputs, especially labor, in the short run, but to decrease inputs in the long run, while tilting the mix of inputs towards capital and nonproduction labor. Favorable technology shocks do not significantly increase measured TFP at any horizon, except for a subset of industries dominated by process innovations, suggesting that available price data do not capture productivity improvements due to product innovations. Technology shocks explain only a small fraction of input and TFP volatility at business cycle horizons.

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I. INTRODUCTION

The "real business cycle" approach to short-run fluctuations, pioneered by Kydland and Prescott (1982) and Long and Plosser (1983), has dominated the academic business cycle literature over the last decade and a half. Kydland-Prescott and Long-Plosser were seminal in several respects. First, they reintroduced the Schumpeterian idea that stochastic technological progress could generate business cycles. Second, they argued that one could explain fluctuations using a frictionless neoclassical framework in which business cycles are optimal and therefore require no smoothing by policymakers. Third, they argued that business cycles could and should be explained using dynamic stochastic general equilibrium models in which preferences and production are explicitly spelled out in a way consistent with microeconomic first principles, such as optimizing behavior.

The real business cycle literature has broadened considerably since Kydland-Prescott and Long-Plosser. Recent research has introduced frictions such as imperfect competition (e.g. Rotemberg and Woodford (1995)), increasing returns to scale (e.g. Farmer and Guo (1994)) and price stickiness (e.g. Kimball (1995)), as well as alternative sources of shocks, such as government spending (e.g. Christiano and Eichenbaum (1992)), monetary policy (e.g. Christiano and Eichenbaum (1995)), and animal spirits (e.g. Schmitt-Grohe (1997)). The idea that business cycles should be analyzed using explicit dynamic stochastic general equilibrium models seems destined to be the main lasting contribution of Kydland-Prescott and Long-Plosser's work.

Meanwhile, the profession has largely ignored the empirical question of what role technology shocks actually play in business cycles. I believe that this is unfortunate, for four reasons. First, the idea that new products and processes are introduced at a time-varying rate is inherently plausible, at least at the disaggregated industry level. Second, much recent research exploring the effects of frictions on business cycle propagation still assumes that cycles are driven by technology shocks (e.g. Cogley and Nason (1995); Horvath (1997); Carlstrom and Fuerst (1997)). It would be useful to know if this modelling strategy has any empirical foundation. Third, while few would argue anymore that technology shocks are the *only* source of business cycles, it would still be useful to know if technology shocks can explain *some* part of fluctuations, particularly given that monetary, oil price and other observable shocks seem unable to account for a large fraction of observed cyclical variation in output (Cochrane (1994)). Finally, even if technology shocks are not responsible for a large share of volatility, the response of the economy to technology could help distinguish between competing views of the economy's propagation mechanisms. In the baseline one-sector flexible-price RBC model, technology shocks shift out the production possibilities frontier, inducing short-run increases in investment, labor and materials. In multisector models, industry technology shocks reduce input prices to downstream sectors, inducing increases in downstream input and output. Meanwhile, Gali (1996) and Basu, Fernald and Kimball (1997) demonstrate that favorable technology shocks may reduce input use in the short run if prices are sticky; intuitively, if prices do not fall, output will be unchanged and inputs must fall to accomodate improved TFP. Thus, one can potentially distinguish between sticky and flexible price models by examining whether technology shocks increase or decrease input use.

To date, the empirical case for technology has largely been made indirectly, by showing that plausibly calibrated models driven by technology shocks can produce realistic patterns of volatility and comovement. Of course, these quantitative exercises, while informative, do not tell us what technology shocks actually do. Two pieces of more direct evidence are that measured total factor productivy (TFP) is procyclical and that aggregate output potentially has a unit root, suggesting that at least some output shocks are permanent. However, it is now well known that neither of these facts prove that technology is important to business cycles. Observable non-technology shocks cause procyclical movements in TFP, consistent with imperfect competition, increasing returns to scale, procyclical factor utilization, or procyclical reallocation of factors to high productivity sectors (e.g. Hall (1988); Evans (1992); Burnside, Eichenbaum and Rebelo (1995); Basu and Fernald (1997)). Meanwhile, demand shocks can have permanent effects on output in endogenous growth models (e.g. Stadler (1990)); and in any case, a unit root is consistent with transitory shocks driving an arbitrarily large fraction of short-run variation (Quah (1989)).

This paper takes a more direct approach to assessing what technology shocks do, an approach inspired by the large literature estimating the impact of monetary policy shocks on the economy (e.g. Christiano, Eichenbaum and Evans (1998)). Using annual panel data for 19 US manufacturing industries from 1959-1991, I employ vector autoregressions (VARs) to document the dynamic impact of shocks to two observable indicators of technological change: research and development (R+D) spending, and patent applications. R+D measures the amount of input devoted to innovative activity, while patent applications measure inventive output. Previous studies (e.g. Griliches and Lichtenberg (1984); Lichtenberg and Siegel (1991); Scherer (1993)), as well as results reported below, suggest that variation in R+D and patenting is related to long-run variation in productivity growth across firms and industries. Moreover, industry-level R+D and patents display nontrivial short-run fluctuations, as can be seen in Figure 1, which plots log real R+D and log patent applications by industry of manufacture and use for the US aerospace industry. If technological progress is truly stochastic, then fluctuations in R+D should in part reflect variation in the perceived marginal product of knowledge, while fluctuations in patents should in part reflect shocks to the success of research activity. I use these fluctuations to estimate how a typical industry's inputs and TFP respond over time to technology shocks, and to quantify the share of industry volatility due to technology shocks. I estimate the impact of both own technology shocks and technology shocks in upstream input-supplying industries.

To be sure, fluctuations in R+D and patent applications may not be due to technology shocks alone. Griliches (1989), for instance, argues that patenting fluctuations in the US are in part responses to factors such as changes in patent law and changes in the efficiency and resources of the US Patent Office. Both R+D and patent applications, meanwhile, are a type of investment, and as such they may respond endogenously to output shocks, either because of financial market constraints or because current shocks are positively correlated with the future marginal product of capital. My preferred VAR specifications address these concerns by including time dummies in the regressions and by placing the technological indicators last in the Choleski ordering used to decompose the VAR innovations into orthogonal components. The time dummies remove fluctuations in R+D and patent applications due to aggregate factors unrelated to true technological progress, such as changes in the number of patent examiners, provided that these factors affect all industries equally. My impulse responses therefore measure the impact of industry-specific technology shocks on industry-specific fluctuations in inputs and TFP, while my variance decompositions estimate the contribution of technology shocks to idiosyncratic industry fluctuations. Placing technology last in the ordering, meanwhile, defines technology shocks as the component of R+D or patenting orthogonal to both lagged technology and lagged and contemporaneous inputs and TFP. Empirically, innovations to industry output are positively correlated with innovations to both R+D and patent applications; placing technology last assumes that this contemporaneous comovement reflects an accelerator mechanism running from industry activity to technology, rather than an instantaneous impact of technology shocks on output. This assumption seems inherently plausible given the likely lags between R+D spending, invention, and diffusion of a new technology (Gort and Klepper (1982)).

My main empirical findings are as follows. First, favorable technology shocks --increases in the orthogonal components of R+D and patents-- tend to increase input use, especially labor, in the short run, but to reduce inputs in the long run. Second, technology improvements tend to encourage substitution towards capital relative to materials and labor, as well as substitution towards nonproduction relative to production labor. These results are consistent with recent cross-sectional studies establishing a complementary long-run relationship between technological change and equipment (Delong and Summers (1991)) and skilled labor (Berman, Bound and Griliches (1994)). Third, favorable technology shocks do not significantly increase measured TFP at any horizon, and indeed in some cases reduce TFP. This suggests that procyclical movements in TFP have little to do with the introduction of new products and processes. Fourth, technology shocks explain only a small share of idiosyncratic industry volatility of inputs and TFP at business cycle horizons. This result is bad news for technology-shock driven models, particularly given that industry-specific technology shocks are likely to explain industry-specific volatility better than aggregate volatility (Horvath (1997)). However, my results could be consistent with models in which technology contributes to low-frequency fluctuations (e.g. Jovanovich and Lach (1997)); or with models in which the important "real" shocks come from strikes, weather, cartel behavior, and so on; or with models in which "technology shocks" are not due to stochastic scientific and engineering developments, but to stochastic movements in management techniques or industrial organization that cause a given set of inputs to be more or less efficient. Finally, I find that technology improvements are more likely to raise TFP and reduce prices in industries characterized by process innovations than in industries dominated by product innovations. This suggests that my failure to find strong effects of technology on TFP may be due in part the failure of available price data to capture productivity gains caused by quality improvements and new product introductions.

Two other recent papers (Gali (1996) and Basu, Fernald and Kimball (1997)) also investigate the short-run impact of technology shocks, in both cases using aggregate data. Gali estimates a structural vector autoregression for labor productivity and labor input in the US, identifying technology shocks by assuming that only technology affects long-run productivity. Basu *et al*, meanwhile, correct industry-level TFP for variations due to increasing returns to scale, imperfect competition and cyclical factor utilization, then measure aggregate technology as an appropriately-weighted average of sectoral technology. Interestingly, Gali and Basu *et al.* both find that favorable technology shocks reduce input use in the short run, consistent with sticky prices but contrary to my results.

These two papers represent a quantum advance over existing literature. Nevertheless, one might disagree with their methodologies for measuring technological change. Gali's approach rests heavily on the assumption that demand shocks cannot affect productivity in the long run. This assumption is inconsistent with both endogenous growth models and with models in which recessions "cleanse" the economy by wiping out low-productivity firms (e.g. Caballero and Hammour (1994 and 1996)). Cleansing models, in particular, predict that favorable demand shocks will reduce long-run productivity, and Gali himself has in the past argued for such an interpretation of the data (Gali and Hammour (1992)). Interestingly, my impulse response functions suggest that input innovations lead to short-run increases in TFP, consistent with increasing returns or procyclical utilization, but long-run decreases in TFP, consistent with cleansing models.

Basu *et al*'s approach, meanwhile, does not rely on long-run restrictions. It does, however, rely on the idea that TFP fluctuations are valid measures of stochastic technological progress at the two-digit industry level, once one corrects for increasing returns, imperfect competition and cyclical factor utilization. This idea seems plausible, but it is not necessarily true, given that fluctuations in "corrected" sectoral TFP could still be due to non-technology sources such as measurement error, within-sector factor reallocations, or inadequate corrections for increasing returns or cyclical utilization. Basu *et al*'s methodology would be more convincing if their corrected measure of technology could be linked to some sort of outside measure of technological progress, such as anecdotal evidence on the timing of particular technical changes in particular industries.

The remainder of the paper proceeds as follows. Section II describes the data. Section III examines long-run and contemporaneous relationships between technological progress and my measures of innovative activity, largely to connect my work to previous studies. Section IV presents evidence from VARs and section V concludes.

II. DATA DESCRIPTION

My goal is to examine the time series interactions between measures of technological change, such as patents and R+D, and measures of economic activity. Ideally, I would estimate these interactions using aggregate data for a single country, following the empirical literature on monetary policy. However, this approach is not feasible in my case. The only readily available data for patents and R+D are annual rather than quarterly or monthly, implying short aggregate time series. Even if higher frequency data could be constructed, it is not clear that it would be useful, given that the impact of technological change on the economy is likely to operate at a somewhat lower frequency than the impact of monetary shocks. To obtain sufficient degrees of freedom to estimate the impact of technology shocks with reasonable precision, I use panel data for 19 manufacturing industries covering 1959-1991, exploiting the fact that technological developments are not perfectly synchronized across industries. An alternative, worth pursuing in future work, would be to use annual aggregate data for a panel of countries, or for panels of both countries and industries.

Data on R+D by industry is taken from the National Science

Foundation's annual survey of US firms. I examine only company-financed R+D. Previous research using cross-sections of industries and firms (e.g Terleckyj (1975); Lichtenberg and Siegel (1991)) has shown that long-run productivity growth is related to company-financed R+D, but not to federally-financed R+D, suggesting that public R+D dollars are spent inefficiently or that they are spent in areas, such as defense or space exploration, where productivity measurement is difficult. I convert nominal R+D to 1991 dollars using the GDP deflator, then convert real R+D flows to an R+D capital stock, following Griliches (1973) and most other subsequent research. I employ a linear capital accumulation equation, assuming a 15 percent annual depreciation rate and setting the 1959 stock equal to the 1959 flow divided by 0.15 plus the industry's average R+D growth over the sample period; these assumptions are standard in recent literature (e.g. Lach (1995), Keller (1997)). Empirical results are similar if I use real R+D flows instead of R+D stocks. As a timing convention, I include R+D spending in year t in the R+D stock for year t, so that I can interpret the correlations between R+D and other variables as reflecting a contemporaneous response of R+D to industry activity. I use data for 19 manufacturing industries; these are listed in Table 1 along with sample means of real R+D flows and the growth rate of the R+D stock. The largest flows of company R+D are found in automobiles, electronics, and computers; the fastest-growing R+D stocks are in drugs, electronics, computers, and instruments. Note that my baseline sample omits nonmanufacturing industries as well as some manufacturing industries (tobacco, printing and publishing, leather, and miscellaneous manufacturing) whose R+D data are lumped together by the NSF. The share of overall R+D accounted for by these sectors is trivial for most of my sample period.

I must mention two problems with this data. First, to avoid disclosure of individual firms' operations, the NSF suppresses some industry-year observations. In virtually all such cases, the NSF suppresses either company-financed or total (including federally financed) R+D, but not both, so that I can interpolate gaps in company R+D using growth of total R+D. Second, the NSF data is collected at the company level. All R+D spending performed by a company is assigned to the industry in which the company had the most sales, even if part of the R+D was conducted in establishments belonging to another industry. Given that R+D is typically performed in large conglomerated firms, the assignment of R+D to particular industries is presumably subject to error. Particularly troubling is the fact that a given firm's industry classification can change over time as its pattern of sales changes, creating the possibility of large movements in measured industry-level R+D spending unrelated to actual changes in spending at the establishment level. Griliches and Lichtenberg (1984) attempt to overcome this problem by using R+D data grouped by applied product field rather than by industry of origin. Unfortunately, the reporting requirements of the NSF's product field survey were burdensome on participating firms, leading to spotty coverage. The survey was reduced from annual to biannual beginning in 1978, and was discontinued in 1986.

Patent data for US industries is not routinely available. The reason is that the US patent office assigns new patents to technological fields, but not to industries. Estimating patents by industry for the US thus requires a mapping from technological fields into industries. The most satisfactory mapping available is the Yale Technology Concordance (YTC), described by Kortum and Putnam (1997). This concordance uses the fact that the Canadian patent office assigns patents to technological fields, to industries of manufacture, and to industries of use; for instance, a new farm tractor invented in an aerospace establishment would be assigned to the agricultural machinery sector (industry of manufacture) and to agriculture itself (industry of use). The YTC estimates mappings between technological field and industries of manufacture and use using the Canadian data, then applies the Canadian mapping to US patents by technological field. For this study, I use annual data on US patent applications grouped both by industry of manufacture and by industry of use, generously provided by Sam Kortum. I convert the annual flows of patents to stocks using the same method as for R+D; empirical results again are similar if I use flows instead of stocks. Note that patents grouped by date of application are superior to patents grouped by date of grant, both because application presumably coincides with the economic viability of an innovation, and because historically there have been long and variable lags between application and granting in the US, caused in part by changes in the resources of the US patent office (Griliches (1989)).

I must again acknowledge potential problems with this data. First, the assignment of US patents to industries is presumably not perfect. The mapping between technological fields and industries probably varies between the US and Canada as well as over time. Kortum and Putnam (1997) show that the estimated Canadian mapping forecasts Canadian industry patents out of sample reasonably well, alleviating these concerns somewhat but not entirely. Second, the distinction in the data between industry of manufacture and industry of use is not as sharp as one might hope. Ideally, I would like to interpret manufacture patents as "product innovations" and use patents as "process innovations". However, conversations with Sam Kortum suggested that this is not entirely correct; for instance, process innovations often wind up being assigned the same industries of manufacture and use even if no new product is created, while new products with broad applicability often wind up being assigned no industry of use. My sense is that we can at least safely assume that manufacture patents contain a higher fraction of product innovations than do use patents, and that use patents contain a higher fraction of process innovations than do manufacture patents.

I present sample means for patent flows and patent stock growth in Table 1. The flows of both manufacture and use patents are highest in nonelectric machinery and electronics, while patent stocks grow most rapidly in drugs and computers. Notice that manufacture patent flows exceed use patent flows in most industries and for my sample as a whole; this reflects the fact that many product innovations originating in manufacturing are used in nonmanufacturing, while few innovations originate in nonmanufacturing. The table also documents the fact, discussed in Griliches (1989) and Kortum (1993), that patent stocks have grown more slowly in the postwar US than R+D stocks, or equivalently that the amount of real of R+D per patent has been steadily rising. Some observers assert that this trend is evidence of vanishing technological opportunities; others argue that the cost of patenting has risen secularly and that patenting has become more concentrated in high-value innovations. Recall that my VARs include time dummies; this will control for any economy-wide changes in the cost or benefits of patenting that have affected the ratio of inventive activity to patents.

In addition to examining the impact of own R+D and patents, I examine the impact of innovations in upstream industries. I construct these measures using data from the 1977 US input-output study, following the methods used by Terleckyj (1975), Keller (1997) and others. I begin by constructing a 19-by-20 matrix whose element (i,j) shows the total flow of goods in 1977 from sample industry i to sample industry j, including both intermediate and capital flows; I describe the construction of total flow matrices from raw input-output data in Shea (1991 and 1993). The 20th column combines flows to omitted manufacturing industries, nonmanufacturing industries, private consumption, and government. I set diagonal elements to zero, then divide by row sums to obtain the shares of external demand for each sample industry accounted for by each other sample industry. I then multiply these demand shares by each industry's R+D and patent flows, to obtain the implicit "flow" of R+D and patents to and from each sample industry. Taking column sums gives me an estimate of the flows of upstream R+D and upstream patent applications to each manufacturing industry in any year. I cumulate these flows into stocks using the methods described above. These measures omit R+D or patents coming from omitted industries; as mentioned earlier, however, these industries account for little innovative activity for most of my sample period.

My measures of TFP and inputs for manufacturing industries come from the NBER productivity data base, described in Bartlesman and Gray (1996). The NBER data includes annual measures of gross output and capital, labor and materials inputs for 450 four-digit manufacturing industries. I measure labor as total employment multiplied by hours worked per production worker, assuming that production and nonproduction hours per worker are perfectly correlated. I define total input as a Divisia index of capital, labor and materials growth, weighting using factor shares in gross output and measuring the capital share as a residual. TFP growth is defined as output growth minus input growth. I measure input and TFP growth at the four-digit level, aggregate up to the 19 industries listed in Table 1 using shares in nominal gross output, then convert growth rates to level indices. Below, I examine the dynamic impact of technology shocks both on total input and on capital, labor and materials separately, premultiplying log capital, labor and materials by their shares in nominal gross output in order to avoid having to impose the condition that factor shares in production are identical across industries.

III. PRELIMINARY EVIDENCE

This section examines the univariate time-series properties of my data, and replicates previous work examining cross-section and contemporaneous time-series relationships between technology and TFP. My baseline data are annual observations for 19 manufacturing industries from 1959-1991 on TFP, total input and its share-weighted capital, labor and materials components, stocks of own R+D, manufacture patents and use patents, and stocks of upstream R+D, manufacture and use patents.

Table 2 presents univariate time series evidence. For each series, I perform an Augmented Dickey-Fuller test of the null hypothesis that the series has a unit root in log levels, including three lagged growth rates to correct for serially correlated errors. I include sector-specific intercepts and time dummies in each specification, and experiment with including sector-specific time trends; all other coefficients are constrained to be equal across sectors. Since these are panel data, I cannot apply the usual Dickey-Fuller critical values; I instead use the formula provided in Levin and Lin (1992), which with 19 industries implies a 5 percent critical value of -7.093 and a 10 percent critical value of -6.816. According to Table 2, I can never reject the null of a unit root when I include only sectoral intercepts and time dummies. However, I can reject a unit root in seven of eight cases when I include sector-specific trends. I conclude that my data are stationary around trends that differ across sectors.

Table 3 looks at the long-run relationship between technology and TFP growth. I estimate cross-section OLS regressions of mean TFP growth on a constant and the mean growth rates of my technology indicators, taken one at a time; the sample size for each regression is 19. The coefficients on own R+D and own manufacture patent growth are positive and significant at 10 percent, while the coefficients on own use patent growth as well as upstream use and manufacture patent growth are positive and significant at 5 percent. My sample is too small to allow for multivariate analysis, and the results are fragile; omitting computers, for instance, reduces the coefficient on technology in all cases, and renders the own R+D results insignificant. Still, these results suggest that my technology indicators capture something about technological progress. My findings are consistent with Griliches and Lichtenberg (1984), Scherer (1984 and 1993), and Lichtenberg and Siegel (1991), who find that R+D and productivity growth are positively related across firms and industries, and with Terleckyj (1975) who reports a significant positive relationship across industries between TFP growth and upstream R+D. Notice that use patents are more strongly related to TFP growth than manufacture patents, suggesting that process innovations may be better captured by available data than product innovations, a theme to which I return below.

Table 4 estimates contemporaneous time series relationships between TFP and technology indicators in log levels, while Table 5 does the same in growth rates. I include sectoral intercepts and time dummies in the levels regressions, and experiment with sector-specific trends; I include a constant and time dummies in the growth rate regressions, and experiment with sectoral intercepts. Results omitting sectoral trends in Table 4 suggest strong, positive contemporaneous relationships between TFP and all six technology indicators. However, including sectoral trends weakens the relationship substantially for own R+D and use patents, and reverses the sign in the other four cases. Similarly, in Table 5 there is a strong positive relationship between TFP growth and technology growth when I control only for time dummies, but this relationship vanishes when I add sectoral intercepts. I conclude that cross-industry differences in trend productivity growth are positively related to cross-industry differences in trend technology growth, but that once I control for these differences there is little correlation between TFP and technology. My results contradict Lach (1996), who reports a contemporaneous positive relationship between patent stock growth and TFP growth in a sample similar to mine, as well as Griliches and Lichtenberg (1984), who find no time series relationship between TFP and R+D even when omitting sectoral trends.

Tables 4 and 5 suggest that there is no contemporaneous "within-industry" relationship between TFP and technology in annual data. Table 6 asks whether such a relationship exists over a longer horizon, by regressing "medium-run" TFP growth on technology growth measured over the sixteen-year intervals 1960-75 and 1976-91. There are two observations per industry, implying a sample size of 38. In the first column, I control only for a constant and a dummy for the second period; these results suggest a positive and significant relationship between TFP and technology growth in the medium run. However, these results rely on both cross-industry and within-industry variation. Adding a sectoral fixed effect in the second column makes the relationship between TFP and technology insignificant, as standard errors rise substantially in all cases and point estimates fall substantially in five of six cases. These results suggest that most of the variation in medium-run technology growth is cross-industry rather than within-industry, and that within-industry medium-run variation in technology and TFP are only weakly related. I obtain similar results when I experiment with different starting and ending dates, as well as with four- and eight-year horizons.

One might wonder if Tables 4 through 6 obviate the need for any further investigation of time-series relationships between TFP and technology. The answer is no. Had I found a robust positive contemporaneous relationship between (say) R+D and TFP, I could not have concluded that R+D shocks cause TFP to rise, because of potential omitted variables bias; shocks to industry output could raise measured TFP due to (say) cyclical utilitzation, while at the same time increasing R+D for accelerator reasons. Similarly, the absence of a contemporaneous relationship does not prove that R+D has no impact on TFP, since such an impact is likely to emerge only with a lag. Both of these problems can be addressed by using vector autoregressions.

IV. VAR EVIDENCE

In this section I present results from a series of vector autoregressions using annual industry panel data on inputs, TFP and technological indicators from 1959-1991. All variables are in log levels, following the panel unit root tests presented in Table 2, although the impulse response functions in log levels are broadly similar if I estimate using growth rates. All specifications include sector-specific intercepts, sector-specific time trends, and time dummies. The time dummies are intended to control for aggregate shocks that affect R+D and patenting intensity, but are unrelated to true technological progress, such as the changes in the US patent office discussed in Griliches (1989). Of course, time dummies will also remove any variation due to aggregate technology shocks, which may bias my results against technology shock models; fortunately, my results are broadly similar if I omit time dummies. I use four lags; experiments with other lag lengths yielded similar results.

Figures 2 through 4 present the complete set of estimated impulse response functions, along with 1.65 Monte Carlo standard error bands, for three-variable VARs estimated on the manufacturing sample. The VARs are ordered as total input, TFP, and either own R+D (Figure 2), own manufacture patents (Figure 3) or own use patents (Figure 4). I enter technology indicators one at a time for presentational simplicity; results are similar if I enter multiple indicators simultaneously. Placing technology last reflects my belief that shocks to R+D or patenting are likely to affect industry activity only with lags. Placing technology first would generate a significant but small expansionary initial impact of technology on inputs and TFP, but with otherwise similar impulse responses and variance decompositions. Figure 5 breaks the input responses to own technology into disaggregated components, taken from five-variable VARs ordered capital, labor, materials, TFP and technology. Figures 6 and 7 present the responses of input, TFP, capital, labor and materials to upstream R+D and patents; these estimates are similar if I control for input-output weighted measures of upstream input demand, suggesting that upstream technology is not merely proxying for upstream activity. I summarize these impulse responses in Table 7, which lists the sign and horizon of every significant effect of technology shocks on non-technology variables. Table 8 presents Granger causality evidence, while Table 9 presents variance decompositions.

While the results vary somewhat across specifications, some robust patterns emerge. First the impulse responses of TFP to technology are not significantly positive at any horizon, and indeed are significantly negative in the long run for all three upstream technology measures. This result is reinforced in Table 8, which indicate that TFP is Granger-caused only by upstream R+D and upstream use patents (and in these cases with negative coefficients).

Second, the impulse responses of total input to technology tend, if anything, to be positive in the short run but negative in the long run. I find that technology shocks significantly raise inputs in the short run in three of six cases, while significantly decreasing long-run inputs in four of six cases.

Third, the impulse responses of individual inputs (particularly labor and materials) to technology are stronger than the responses for total input, as the disaggregated impacts tend to wash out due to both staggering and conflicting signs. This pattern is mirrored in the Granger causality results, which show that technology shocks forecast total input in only three of six cases, but forecast labor and materials in five of six cases. Favorable technology shocks to increase short-run labor use significantly in five of six cases, while decreasing long-run materials use significantly in five of six cases. Note that shocks to both own and upstream R+D significantly increase capital accumulation in the short run. This result is consistent with Lach and Rob (1996), who find that R+D Granger-causes physical investment in industry panel data, and with Lach and Schankerman (1989), who find the same result in firm-level data. In my data, R+D does not Granger-cause capital, but it does Granger-cause investment.

Fourth, technology shocks explain only a small fraction of input and TFP variation at business cycle horizons. Technology explains less than 2 percent of three-year volatility in all cases, and less than 5 percent of six-year volatility in all but one case. Technology has somewhat more explanatory power at longer horizons, particularly for upstream R+D and upstream use patents; recall, however, that the impulse responses for these cases suggest significant long-run *contractions* of inputs and TFP following favorable technology shocks. The fact that technology explains a larger share of variance at longer horizons is consistent with Jovanovic and Lach (1997), who model technology shocks as having long diffusion lags and find that technology shocks "underexplain" short-run but "overexplain" longer-run volatility.

Along with the results for technology shocks, two other features of my estimates are worth noting. First, own R+D and own patents respond positively and significantly to input shocks; moreover, R+D increases immediately, while patents increase only after five years. One possible interpretation is that industry expansions generate increased R+D immediately, and that this investment eventually leads to an increased flow of patentable inventions. Second, input shocks lead to short-run increases but long-run decreases in TFP. A possible interpretation is that industry expansions raise measured TFP in the short-run due to increasing returns or cyclical utilization, but reduce long-run productivity. An interesting question is how these two features of the data can coexist--if expansions increase R+D and patents, then why don't they increase productivity? One possibility is that expansions raise inventive activity but also allow lower-productivity firms to enter and survive, generating a net decline in productivity.

Results for Input Mix, Worker Mix and Prices

While this paper is primarily concerned with the impact of technology shocks on total input and TFP, technology shocks are likely to affect other variables as well. Conventional models predict that favorable technology shocks reduce the relative price of industry output. Meanwhile, if technology shocks are permanent and the supply of capital is more elastic in the long-run than the supply of labor or materials (as in the baseline RBC model), then favorable technology shocks increase the long-run ratio of capital to other inputs. Finally, some have hypothesized that technological advances have been biased towards skilled workers during the postwar period, either because skilled workers have an advantage in learning new technologies (Greenwood and Yorukoglu (1996)) or because technology shocks are investment-specific and capital is complementary with skill (Krusell, Ohanian, Rios-Rull and Violante (1996)).

Figures 8 and 9 present impulse responses to own and upstream technology shocks for three variables: the "worker mix", defined as the ratio of nonproduction to total employment; the "input mix", defined as the log of the ratio of capital's product (capital raised to the power α_K, where α_K is capital's share of revenue) to labor and materials' product; and the industry's relative price, defined as the implicit gross output deflator divided by the GDP deflator. I assume that increases in nonproduction employment are positively correlated with changes in the ratio of skilled to unskilled employees, following Berman, Bound and Griliches (1994). My input mix variable is one of several ways I could quantify changes in capital relative to other variables; results are similar when I use more familiar measures such as the capital-labor ratio. The impulse responses are taken from four variable VARs in which the new variables are ordered after inputs and TFP but before technology; data for nonproduction employment, total employment and prices are taken from the NBER productivity database.

The results conform to prior intuition in two out of three cases. Favorable technology shocks cause significant long-run substitution towards capital in five of six cases; technology improvements also significantly increase the ratio of nonproduction to total employment in five of six cases, although these increases often occur in the short run rather than the long run. However, the estimated impact of technology shocks on price is not robust; own R+D and own use patent shocks significantly reduce price in the long run, but manufacture patent shocks raise price in the medium run, while upstream use patent shocks raise price in the long run. The fact that use patents (which should reflect process innovations) reduce prices while manufacture patents (which should reflect product innovations) raise prices suggests that available price data might not accurately reflect product innovations, an idea to which I return below.

Results for Nonmanufacturing

My empirical results to this point have relied exclusively on manufacturing industries. However, technology shocks originating in manufacturing, such as the introduction of the jet engine in the late 1950s, often have important downstream impacts in nonmanufacturing. While disaggregated data on own R+D and own patenting in nonmanufacturing industries is not readily available --in part because virtually all R+D and patenting has occurred in manufacturing until very recently-- I can construct measures of upstream technology for nonmanufacturing using the techniques described in Section II. Figures 10 and 11 present impulse responses of inputs and TFP to upstream technology shocks for a panel of 10 nonmanufacturing industries: agriculture; mining; construction; transportation; communications; electric utilities; gas utilities; trade; finance, insurance and real estate (FIRE); and services. Data on inputs and TFP come from an updated version of the KLEM database described in Jorgenson, Gollop and Fraumeni (1987), generously provided by Susanto Basu. Although Jorgenson *et al*'s preferred measure of labor input corrects for variations in labor force composition, I use man hours to be consistent with the manufacturing data. The impulse responses for nonmanufacturing are striking and robust: favorable upstream technology shocks significantly increase capital, labor, materials and total input in the short run, but reduce measured TFP in the short run; inputs and TFP return to trend in the long run. The variance decompositions (available from the author) assign technology a substantial share of volatility of TFP and inputs at the six year horizon, particularly for upstream R+D; however, technology has a much smaller role for output volatility, as the input and TFP effects cancel each other out.

Measurement Error in Price Indices

The fact that favorable technology shocks do not significantly increase measured TFP raises suspicions about the quality of the TFP data. Much recent research has criticized BLS price data for not registering implicit price changes due to quality improvements or new product introductions (e.g. Gordon (1990)), or, in the case of many nonmanufacturing sectors, for not registering price changes at all (e.g.

Baily and Gordon (1988)). If product innovations do not reduce measured prices, they are less likely to increase measured output or TFP; this is especially troublesome given that roughly 80 percent of US R+D is devoted to product rather than process innovation (Scherer (1984)). Similarly, if nonmanufacturing prices are measured poorly or not at all, then upstream innovations that reduce true prices and increase true activity may not raise measured output; if measured inputs rise (perhaps because inputs are easier to measure than output), then measured TFP is likely to fall.

To examine whether measurement errors in prices are important for my results, I divide the 19 sample manufacturing industries into process-innovating versus product-innovating sectors. Table 10 presents the average percentage of R+D spending in gross output over the period 1959-1991, as well as the percentage of process R+D in total R+D spending in 1974, as reported in Scherer (1984). The table indicates that there is a fairly sharp break between process and product innovating sectors, and that the most R+D-intensive industries are typically product-intensive. I assign food, textiles, lumber, paper, industrial chemicals, petroleum, rubber, stone and primary metals to the process-innovating group, and the other ten industries to the product-innovating group. Figures 12 and 13 present the responses of total input, TFP and price to technology shocks for the two groups. The results indicate a sharp distinction between process- and product-innovating industries: for process-innovating sectors, favorable technology shocks induce a significant long-run increase in TFP, a significant long-run decline in price, and a significant long-run decline in inputs; for product-innovating sectors, favorable technology shocks do not raise TFP in any instance, and reduce long-run inputs and prices in only one case. These results suggest that the failure of technology to increase TFP in my full sample may be due to the failure of available data to reflect price declines and productivity gains due to quality improvements and new product introductions. Another interesting result is that process-industry TFP declines significantly in the short run in two of three cases. This result is consistent with models in which technological advances cause a short run productivity decline, as workers move down the new technology's learning curve (e.g. Greenwood and Yorukoglu (1996), Hornstein and Krusell (1996)).

CONCLUSION

This paper's key contribution is to estimate the impact of technology shocks on the economy using R+D spending and patent applications rather than observed total factor productivity to measure technology. The most surprising finding is that favorable technology shocks do not raise measured TFP at any horizon. Taken at face value, this suggests that observed procyclical variation in TFP is entirely due to factors such as increasing returns, cyclical utilization, and factor reallocation, and not at all due to procyclical technology. It also suggests that efforts to measure short-run changes in true technology by "cleansing" measured TFP of movements due to cyclical utilization and so on (e.g. Basu, Fernald and Kimball (1997); Burnside, Eichenbaum and Rebelo (1996)) may be doomed from the start.

Of course, another interpretation of my results is that my R+D and patent data are riddled with measurement error that biases me against finding a significant impact of technology on TFP. While the R+D and patent data are certainly vulnerable to criticism, my results cannot be so easily dismissed. Measurement error should bias me against finding a significant impact of technology on anything. Yet I find that favorable technology shocks have a significant short-run expansionary impact on labor, a significant long-run contractionary impact on total input, and a significant positive impact on capital and nonproduction worker intensity. I also find that technology shocks raise long-run TFP and reduce long-run prices in a subsample of industries dominated by process R+D. These results suggest that the important measurement error is not in R+D or patents, but in output prices. Most R+D in the United States is devoted to product innovations, yet many observers believe that available price data systematically ignore real price declines due to quality improvements and new product introductions. Similarly, a good deal of the impact of industrial R+D is felt in downstream nonmanufacturing sectors, yet many observers argue that price changes of any kind in nonmanufacturing are poorly measured.

It is quite possible, then, that technology shocks are more important to actual output and TFP fluctuations than they are to observed fluctuations. To paraphrase Ed Prescott (1986), theory may be ahead of business cycle measurement. If real business cycle enthusiasts want to convince the profession that technology shocks are genuinely important to business cycles, their first order of business should be to construct historical price series for manufacturing and nonmanufacturing sectors that correct for quality improvements and new product introductions, following the painstaking work of Gordon (1990) on durable goods. Such a project will surely require many hours of research into the history of product innovations in particular sectors, but imagine how different the profession would be today had Friedman and Schwartz (1963) not devoted many hours of research into the history of monetary institutions and monetary shocks.

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TABLE 1

Sample Means

Industry	R+D	R+D Growth	Manu Patents	Manu Patent Growth	Use Patents	Use Patent Growth
Food (SIC 20)	879.1	4.62	311.2	0.63	1085	0.06
Textiles (SIC 22-23)	185.5	3.57	620.9	1.17	994	-0.81
Lumber (SIC 24-25)	152.0	4.81	605.9	0.08	597	-0.05
Paper (SIC 26)	611.7	5.53	482.4	0.04	490	0.08
Industrial Chemicals (SIC 281-2, 286)	3211.7	2.80	3758.8	0.75	2518	0.47
Drugs (SIC 283)	2629.4	7.75	825.5	5.90	1100	2.73
Other Chemicals (other SIC 28)	1053.0	5.27	2517.4	0.54	1261	0.70
Petroleum (SIC 29)	1812.4	2.82	1745.5	-1.30	1659	0.22
Rubber (SIC 30)	693.2	4.01	1586.0	1.03	1348	1.45
Stone (SIC 32)	574.5	3.05	506.8	1.60	557	0.76
Metals (SIC 33)	835.9	1.51	373.1	0.30	795	0.06
Metal Prods. (SIC 34)	684.1	2.06	3737.6	0.18	1979	0.24
Computers (SIC 357)	5172.6	6.66	1114.3	2.70	1333	3.09
Other Nonelec. Equip. (Other SIC 35)	2102.3	5.08	10966.1	-0.15	4084	-0.33
Electronics & Commun. Equip. (SIC 366-7)	5018.4	6.65	5629.4	1.51	4456	1.76
Other Electric Equip. (Other SIC 36)	2043.7	0.99	4154.1	0.41	2779	0.43
Aerospace (SIC 372,6)	4022.4	4.81	276.9	-1.22	392	-0.77
Autos & Other Transp. Equip. (SIC 37)	5701.8	4.37	1972.1	-0.28	2787	-0.09
Instruments (SIC 38)	3100.3	7.42	3626.7	2.33	1268	1.59

TABLE 2

Panel Unit Root Tests

$$\Delta\log(X_{it}) = \gamma_i + \begin{matrix}\text{Other}\\ \text{Deterministic}\\ \text{Terms}\end{matrix} + \beta \log(X_{it-1}) + \sum_{k=1}^{3} \alpha_k \log(X_{it-k}) + \varepsilon_{it}$$

X	--Other Deterministic Terms--- Time Dummies	Time Dummies & Sectoral Trends
TFP	-0.003 (0.007)	-0.174 **(0.022)
Total Input	-0.024 (0.011)	-0.193 **(0.026)
Capital	-0.014 (0.008)	-0.244 *(0.034)
Labor	-0.107 (0.018)	-0.201 **(0.028)
Materials	-0.038 (0.013)	-0.218 **(0.029)
R+D	-0.017 (0.004)	-0.096 **(0.011)
Manufacture Patents	-0.009 (0.003)	-0.092 **(0.011)
Use Patents	-0.014 (0.004)	-0.058 (0.010)

NOTES: this table presents estimates of β from Augmented Dickey-Fuller tests of the null hypothesis that log(X) contains a unit root, using annual panel data for 19 industries from 1959-1991. All regressions include sector-specific intercepts and time dummies; regressions in the right column also contain sector-specific linear time trends. Standard errors are in parentheses. A (*) indicates that β is significant at 10 percent, while a (**) indicates significance at 5 percent. The critical values of 6.816 (10 percent) and 7.093 (5 percent) are taken from the asymptotic formula provided in Levin and Lin (1992).

TABLE 3

Long-Run Evidence

$$\Delta\log(TFP_i) = \gamma + \beta\ \Delta\log(X_i) + \varepsilon$$

X	γ Estimate	β Estimate
R+D	-0.005 (0.009)	0.328 *(0.196)
Manufacture Patents	0.006 (0.004)	0.426 *(0.233)
Use Patents	0.003 (0.003)	1.082 **(0.275)
Upstream R+D	-0.023 (0.021)	0.752 (0.483)
Upstream Manu Patents	-0.005 (0.004)	1.880 **(0.768)
Upstream Use Patents	-0.006 (0.006)	2.345 **(0.837)

NOTES: this table presents estimates of cross-section relationships between long-run total factor productivity growth and long-run growth in technology indicators. Each variable is entered as a mean industry-level growth rate over 1960-1991; the sample size is 19. Standard errors are in parentheses. A (*) denotes significance at 10 percent, while a (**) denotes significance at 5 percent.

TABLE 4

Contemporaneous Evidence: Log Levels

$$\log(TFP_{it}) = \gamma_i + \begin{matrix}\text{Other}\\ \text{Deterministic}\\ \text{Terms}\end{matrix} + \beta \log(X_{it}) + \varepsilon_{it}$$

X	--Other Deterministic Terms---	
	Time Dummies	Time Dummies & Sectoral Trends
R+D	0.334 **(0.041)	0.056 *(0.035)
Manufacture Patents	0.396 **(0.055)	-0.300 **(0.063)
Use Patents	1.102 **(0.073)	0.121 (0.078)
Upstream R+D	0.773 **(0.095)	-0.460 **(0.126)
Upstream Manu Patents	2.121 **(0.217)	-0.441 **(0.149)
Upstream Use Patents	3.289 **(0.250)	-0.784 **(0.263)

NOTES: this table presents estimates of contemporaneous relationships between log levels of total factor productivity and technology indicators, using annual panel data on 19 industries from 1959-1991. All regressions include sector-specific intercepts and time dummies; regressions in the right column also contain sector-specific linear time trends. Standard errors are in parentheses. A (*) indicates significance at 10 percent, while a (**) indicates significance at 5 percent.

TABLE 5

Contemporaneous Evidence: Growth Rates

$$\Delta\log(TFP_{it}) = \gamma + \begin{matrix}\text{Other}\\ \text{Deterministic}\\ \text{Terms}\end{matrix} + \beta\,\Delta\log(X_{it}) + \varepsilon_{it}$$

	--Other Deterministic Terms---	
X	Time Dummies	Time Dummies & Sectoral Trends
R+D	0.132 **(0.049)	0.047 (0.050)
Manufacture Patents	0.195 **(0.074)	-0.070 (0.101)
Use Patents	0.512 **(0.099)	0.052 (0.124)
Upstream R+D	0.235 **(0.123)	-0.058 (0.142)
Upstream Man. Patents	0.530 **(0.217)	-0.291 (0.254)
Upstream Use Patents	1.140 **(0.280)	-0.057 (0.367)

NOTES: this table presents estimates of contemporaneous relationships between growth rates of total factor productivity and technology indicators, using annual panel data on 19 industries from 1960-1991. All regressions include a constant and time dummies; regressions in the right column also sector-specific intercepts. Standard errors are in parentheses. A (*) indicates significance at 10 percent, while a (**) indicates significance at 5 percent.

TABLE 6

Medium-Horizon Evidence: Sixteen Year Growth Rates

$$\Delta\log(TFP_{it}) = \gamma + \begin{matrix}\text{Other}\\ \text{Deterministic}\\ \text{Terms}\end{matrix} + \beta\,\Delta\log(X_{it}) + \varepsilon_{it}$$

X	--Other Deterministic Terms--- Time Dummy	Time Dummy & Fixed Effect
R+D	0.285 *(0.154)	0.140 (0.288)
Manufacture Patents	0.297 (0.166)	-0.347 (0.416)
Use Patents	0.960 **(0.233)	0.614 (0.451)
Upstream R+D	0.462 (0.406)	-1.206 (0.872)
Upstream Man. Patents	1.209 **(0.572)	0.149 (0.835)
Upstream Use Patents	2.348 **(0.729)	2.371 (2.078)

NOTES: this table presents estimates of the relationship between medium-horizon growth rates of total factor productivity and technology indicators, using data on 19 industries for two sixteen year periods, 1960-75 and 1976-91. All regressions include a constant and a dummy for the second period; regressions in the right column also include a sector-specific fixed effect. Standard errors are in parentheses. A (*) indicates significance at 10 percent, while a (**) indicates significance at 5 percent.

TABLE 7

Impulse Response Functions: Summary

Significant Impacts of Technology on Industry Activity

	--3 Variable VAR-		------5 Variable VAR------		
Tech Indicator	Total Input	TFP	Capital	Labor	Materials
R+D	↓ 7-10	---	↑ 4	↑ 2-3 ↓ 7-10	↓ 4-10
Manufacture Patents	---	---	↓ 4 ↑ 8-10	↑ 4-5	↓ 8-10
Use Patents	↑ 2 ↓ 9-10	---	↓ 3-10	↑ 2-7	↑ 2 ↓ 8-10
Upstream R+D	↓ 9-10	↓ 7-10	↑ 2-10	↓ 8-10	↓ 6-10
Upstream Manu Patents	↑ 2-7	↓ 7-10	---	↑ 2-6	↑ 2-6
Upstream Use Patents	↑ 2,4-5 ↓ 8-10	↓ 6-10	↓ 9-10	↑ 2-5 ↓ 8-10	↑ 2-5 ↓ 8-10

NOTES: This table summarizes the VAR impulse functions by reporting all cases of a significant (10 percent) impact of technology on industry variables, along with the relevant horizons in years. The impulse responses are calculated from VARs estimated using annual panel data for 19 industries from 1959-1991. The results in the first two columns are based on three-variable VARs ordered as total input, TFP and technology, while the results in the last three columns are based on five-variable VARs ordered as capital, labor, materials, TFP and technology. All VARs are estimated in log levels and include sector-specific intercepts and trends as well as time dummies. The standard errors are computed using Monte Carlo integration.

TABLE 8

Granger-Causality Tests: P-Values

Panel A: Does Technology Granger-Cause Inputs or TFP?

	--3 Variable VAR-		------5 Variable VAR------		
Technology Indicator	Total Input	TFP	Capital	Labor	Materials
R+D	0.21	0.95	0.42	0.01	0.02
Manufacture Patents	0.85	0.51	0.04	0.05	0.13
Use Patents	0.05	0.92	0.01	0.01	0.00
Upstream R+D	0.12	0.07	0.02	0.12	0.01
Upstream Manu Patents	0.01	0.46	0.47	0.03	0.01
Upstream Use Patents	0.00	0.01	0.15	0.00	0.00

Panel B: Do Inputs and TFP Granger-Cause Technology?

	--3 Variable VAR-		------5 Variable VAR------		
Technology Indicator	Total Input	TFP	Capital	Labor	Materials
R+D	0.38	0.62	0.34	0.95	0.63
Manufacture Patents	0.05	0.41	0.58	0.14	0.21
Use Patents	0.11	0.56	0.72	0.25	0.01
Upstream R+D	0.00	0.35	0.04	0.06	0.00
Upstream Manu Patents	0.06	0.48	0.08	0.03	0.51
Upstream Use Patents	0.00	0.32	0.01	0.02	0.16

NOTES: this table presents p-values from Granger Causality tests from technology to industry activity and vice-versa. The tests are based on VARs estimated using annual panel data for 19 industries from 1959-1991.

TABLE 9

Variance Decompositions

Percent of Variance Due to Technology

Tech Indicator	Years	--3 Variable VAR- Total Input	TFP	------5 Variable VAR------ Capital	Labor	Materials
R+D	3	0.05	0.07	0.23	0.66	0.04
	6	0.38	0.06	1.08	0.95	2.06
	9	2.42	0.07	1.20	3.89	4.06
Manufacture Patents	3	0.19	0.16	0.31	0.27	0.37
	6	0.22	0.60	0.53	1.22	0.42
	9	0.23	0.97	1.60	1.25	1.32
Use Patents	3	0.26	0.04	0.54	0.87	0.70
	6	0.28	0.05	2.81	3.49	0.93
	9	0.98	0.19	5.22	4.13	3.49
Upstream R+D	3	0.76	0.44	1.47	0.22	0.16
	6	1.15	2.17	8.04	0.99	2.23
	9	8.21	12.51	20.33	8.01	14.10
Upstream Manu Patents	3	1.00	0.08	0.03	1.38	1.34
	6	3.98	0.25	0.28	4.65	3.94
	9	4.49	1.82	0.39	4.86	3.95
Upstream Use Patents	3	0.60	0.08	0.09	1.09	1.19
	6	2.11	1.48	0.23	3.69	2.97
	9	5.35	10.13	1.38	5.27	5.57

NOTES: This table summarizes the VAR variance decompositions by reporting the share of variance of industry activity variables accounted for by shocks to technology at 3, 6 and 9 year horizons. The variance decompositions are calculated from VARs estimated using annual panel data for 19 industries from 1959-1991. The results in the first two columns are based on three-variable VARs ordered as total input, TFP and technology, while the results in the last three columns are based on five-variable VARs ordered as capital, labor, materials, TFP and technology. All VARs are estimated in log levels and include sector-specific intercepts and trends as well as time dummies.

TABLE 10

Process Versus Product R+D Intensity

Industry	R+D Intensity	Percent Process R+D
Food (SIC 20)	0.2	56.1
Textiles (SIC 22-23)	0.1	61.3
Lumber (SIC 24-25)	1.5	59.0
Paper (SIC 26)	0.7	33.1
Industrial Chemicals (SIC 281-2, 286)	3.4	47.6
Drugs (SIC 283)	8.2	12.0
Other Chemicals (other SIC 28)	1.4	14.6
Petroleum (SIC 29)	1.4	64.0
Rubber (SIC 30)	1.1	48.0
Stone (SIC 32)	0.9	52.5
Metals (SIC 33)	0.5	75.2
Metal Prods. (SIC 34)	0.4	14.6
Computers (SIC 357)	12.5	5.5
Other Nonelec. Equip. (Other SIC 35)	1.2	4.1
Electronics & Commun. Equip. (SIC 366-7)	5.4	21.2
Other Electric Equip. (Other SIC 36)	2.3	11.5
Aerospace (SIC 372,6)	4.4	21.7
Autos & Other Transp. Equip. (SIC 37)	2.6	4.8
Instruments (SIC 38)	5.0	8.0

NOTES: The first column reports the average value of R+D spending as a percentage of nominal gross output over the sample period 1959-1991. The second column reports the fraction of 1974 R+D spending devoted to process R+D, as reported in Scherer (1984).

FIGURE 1: Technology Indicators in the Aerospace Industry

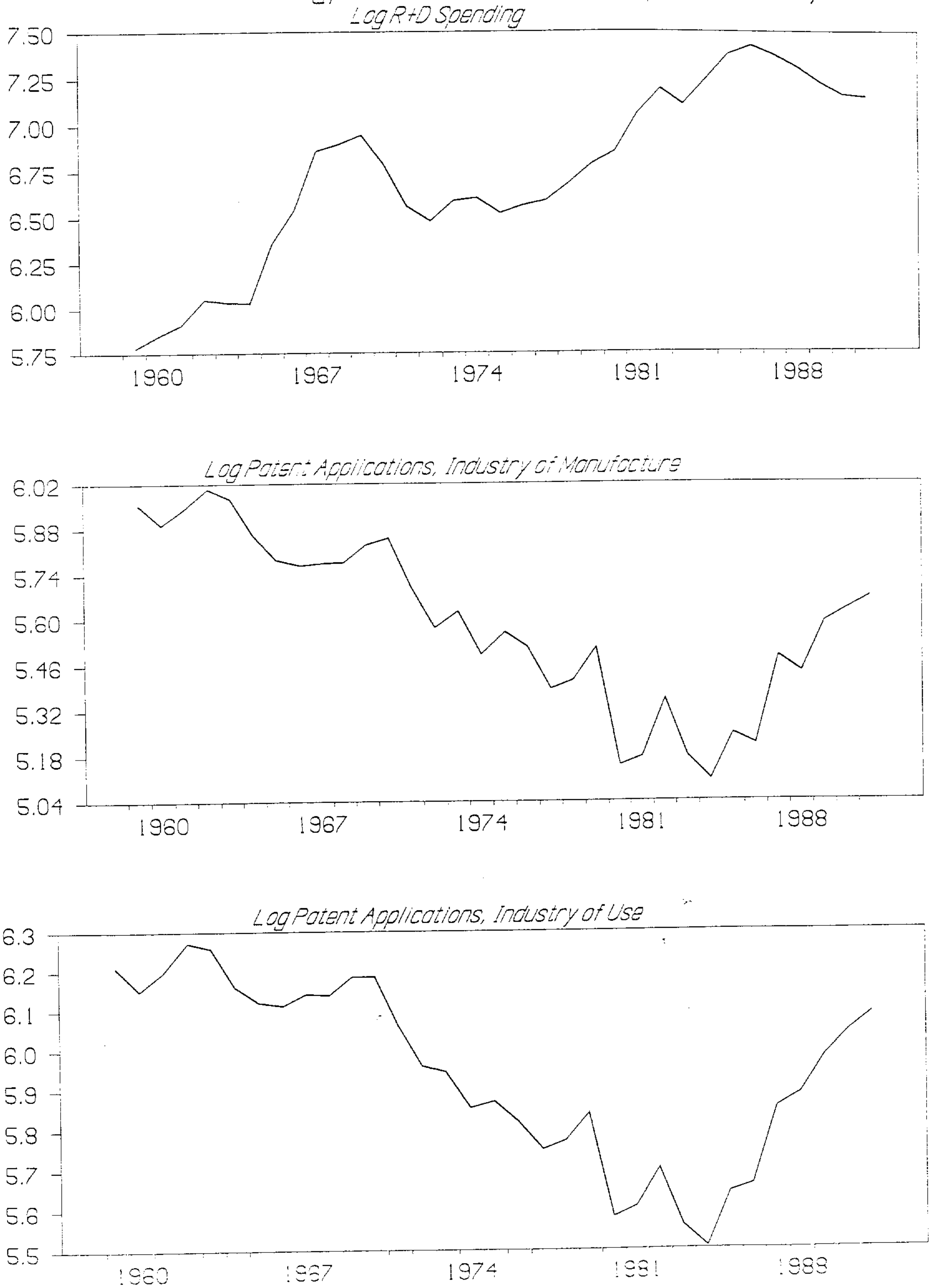

FIGURE 2: Inputs, TFP and R+D

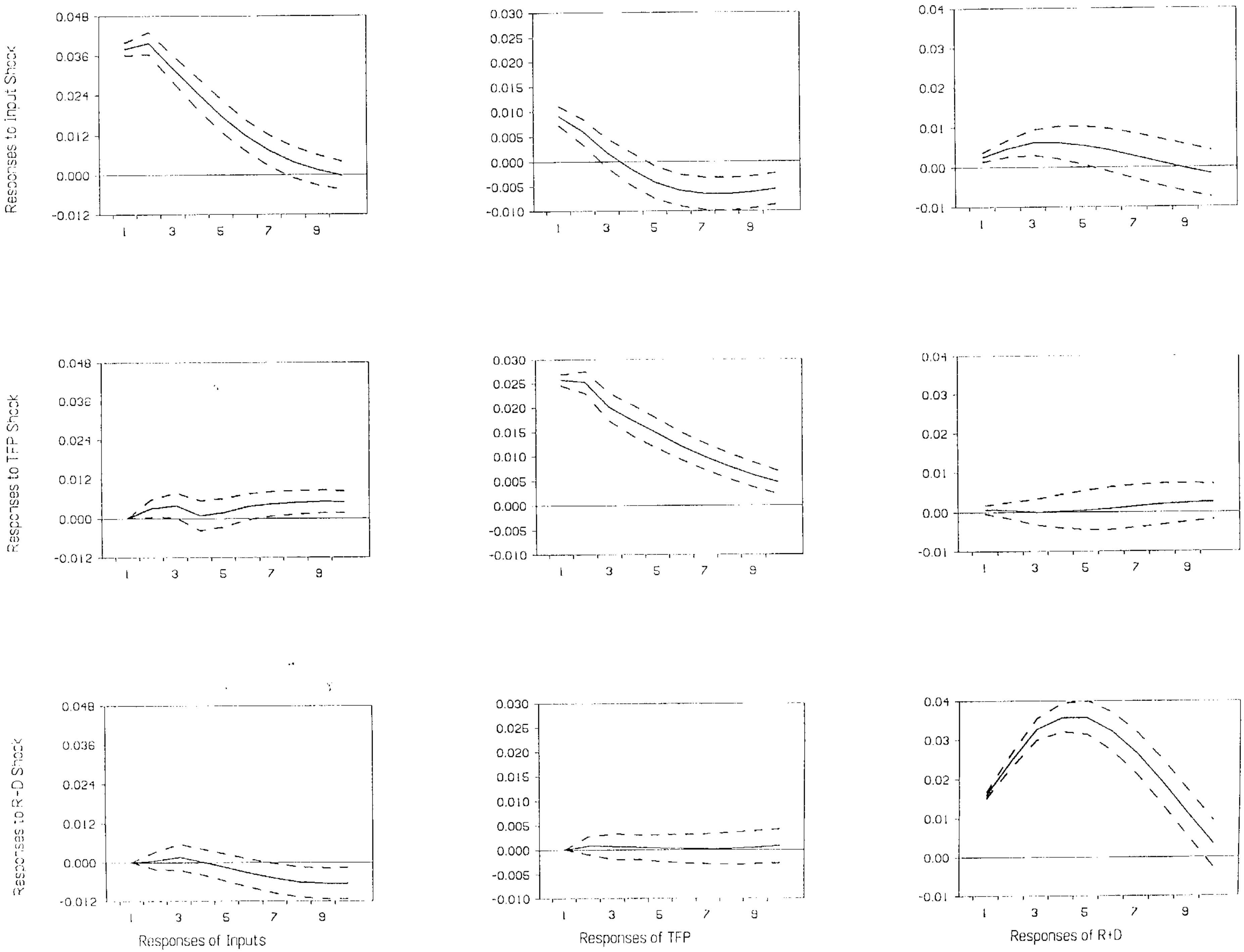

FIGURE 3: Inputs, TFP and Manufacture Patents

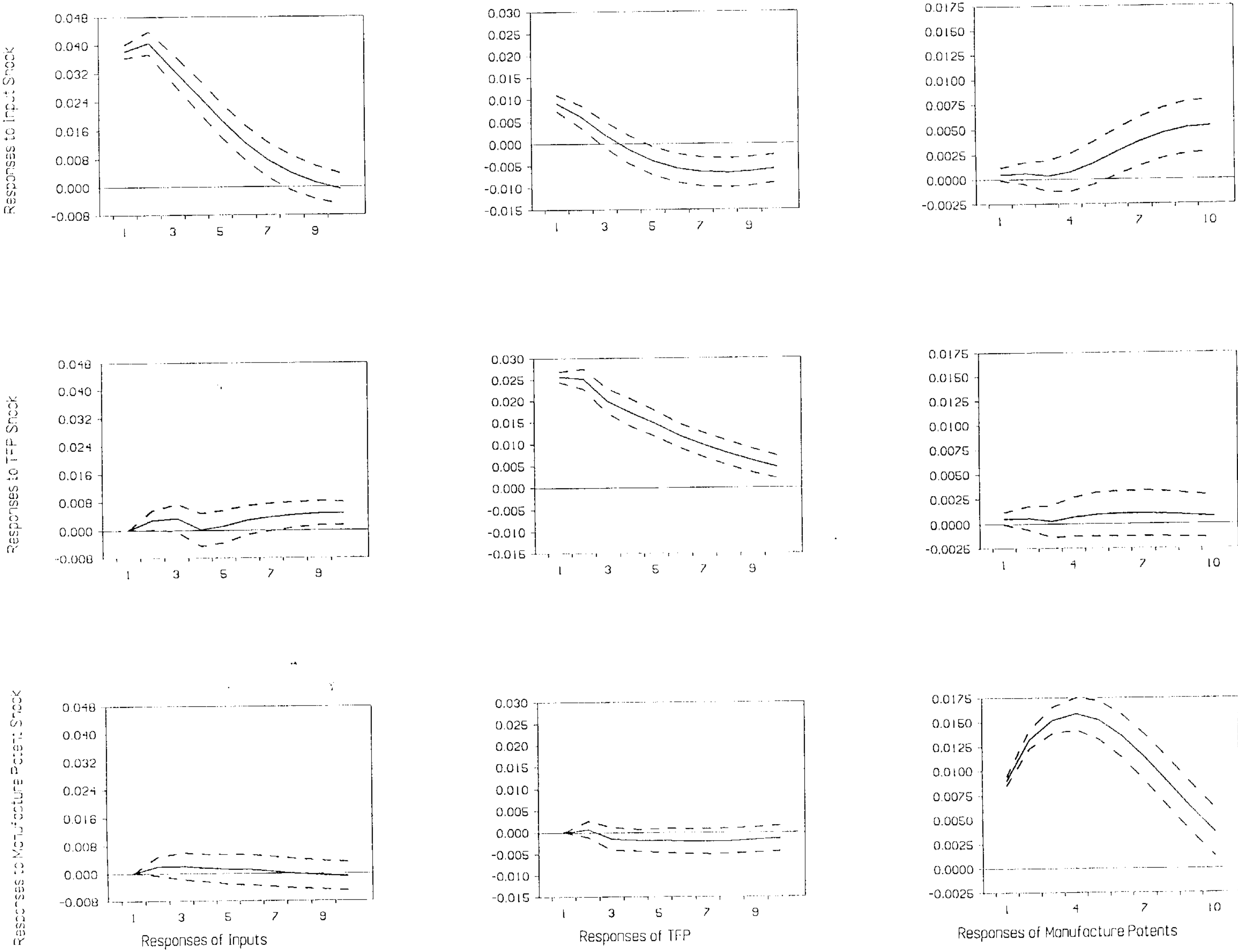

FIGURE 4: Inputs, TFP and Use Patents

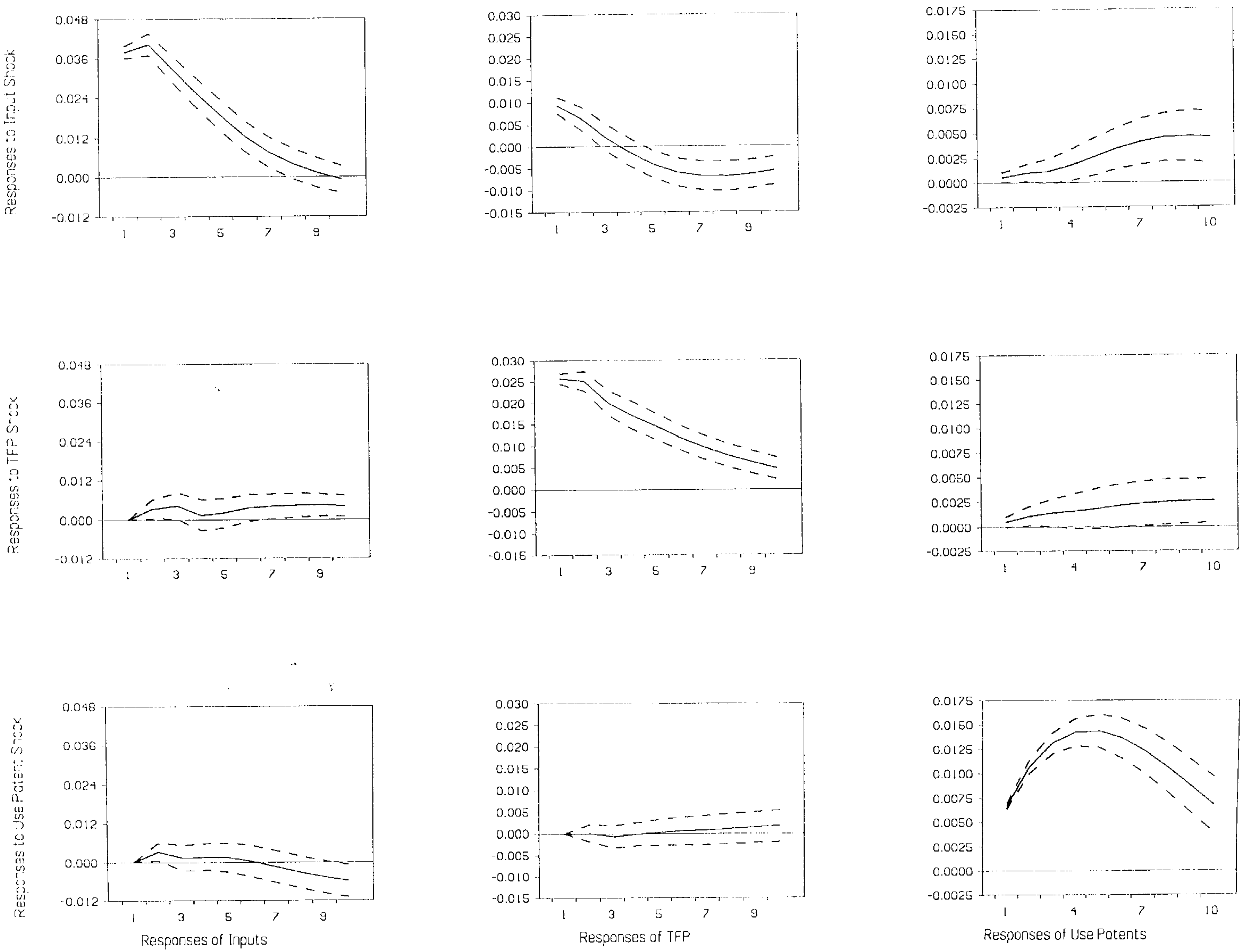

FIGURE 5: Capital Labor, Materials and Own Technology Shocks

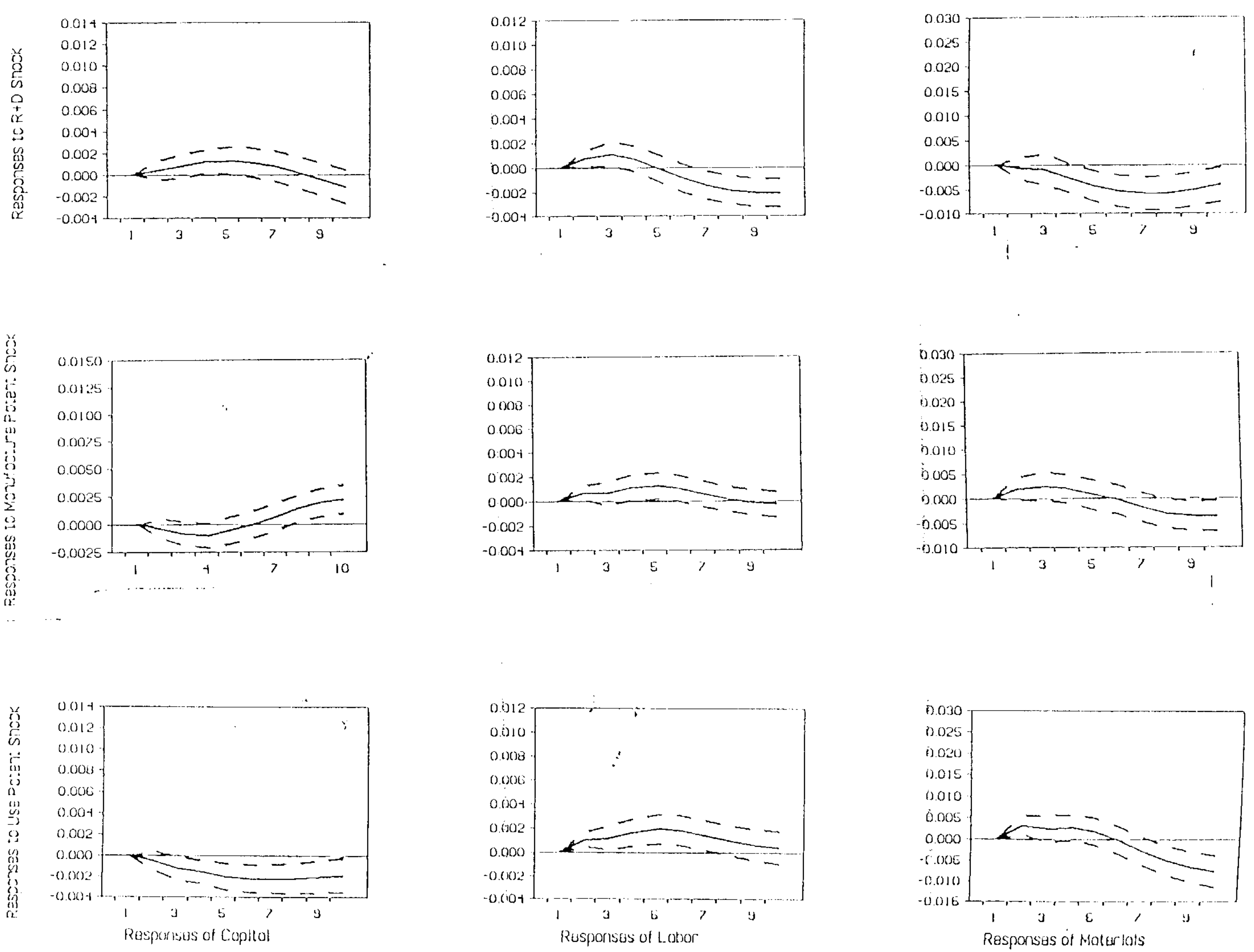

FIGURE 6: Inputs, TFP, and Upstream Technology Shocks

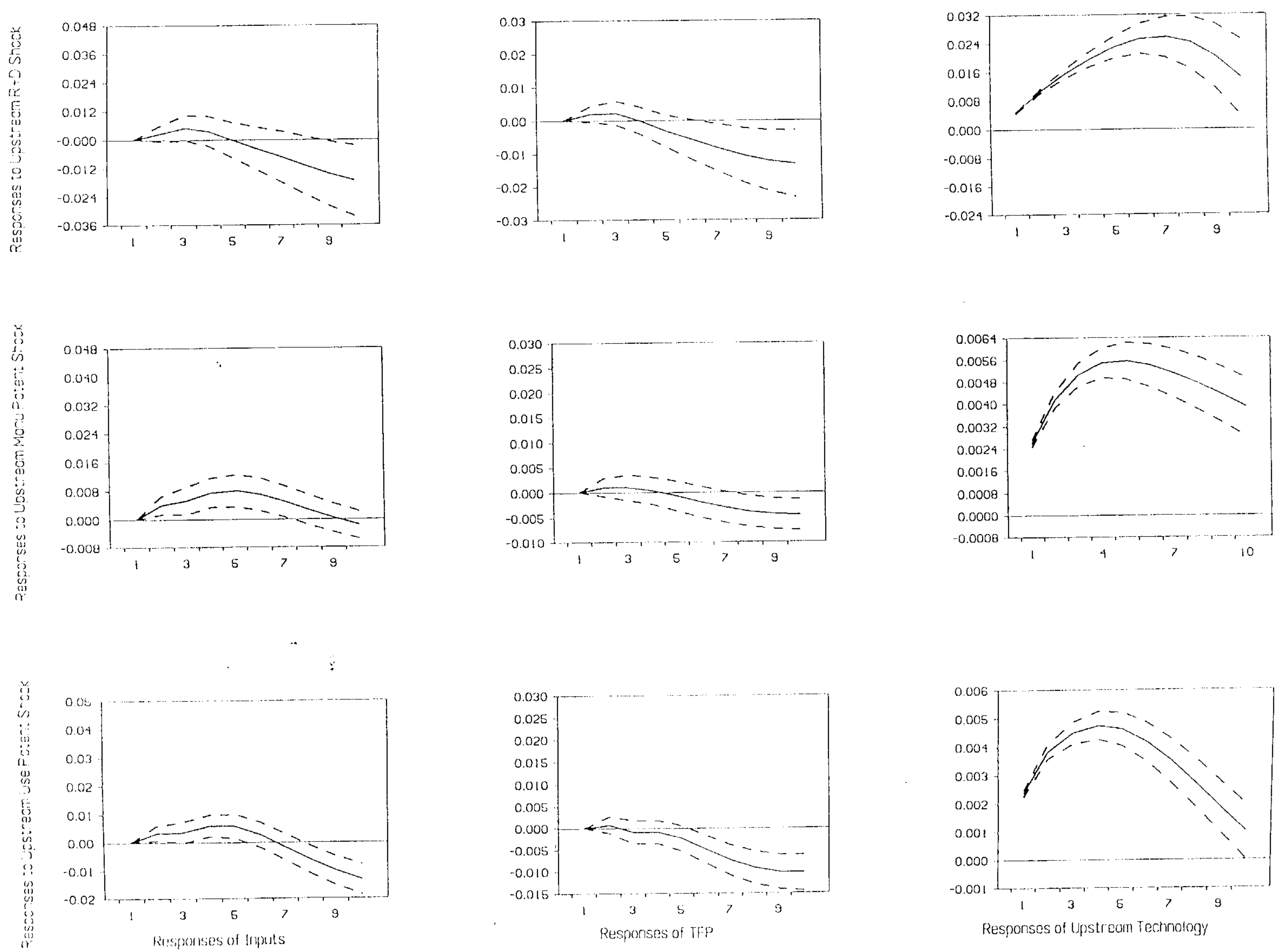

FIGURE 7: Capital, Labor, Materials and Upstream Technology Shocks

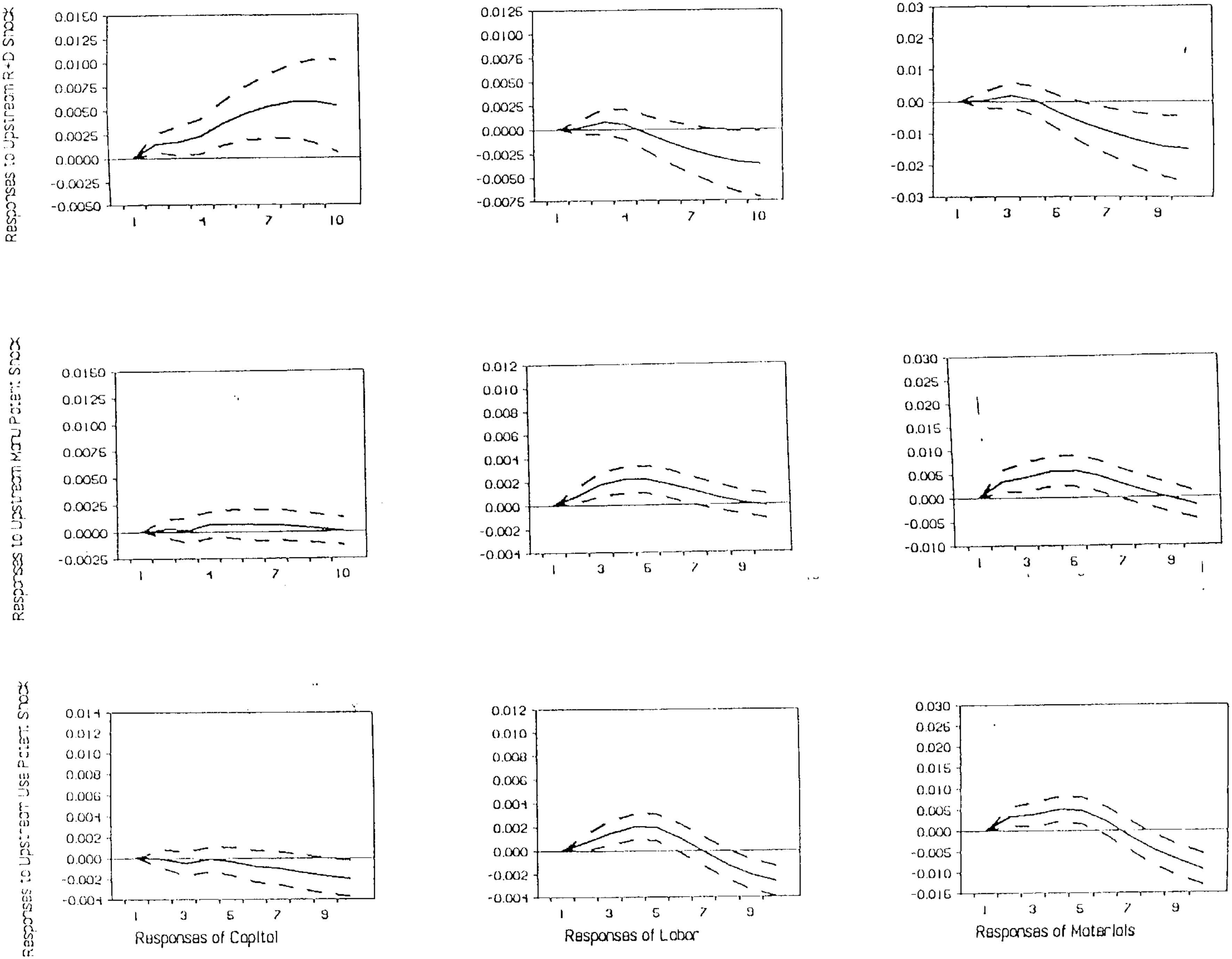

FIGURE 8: Worker Mix, Input Mix, Own Price and Own Technology

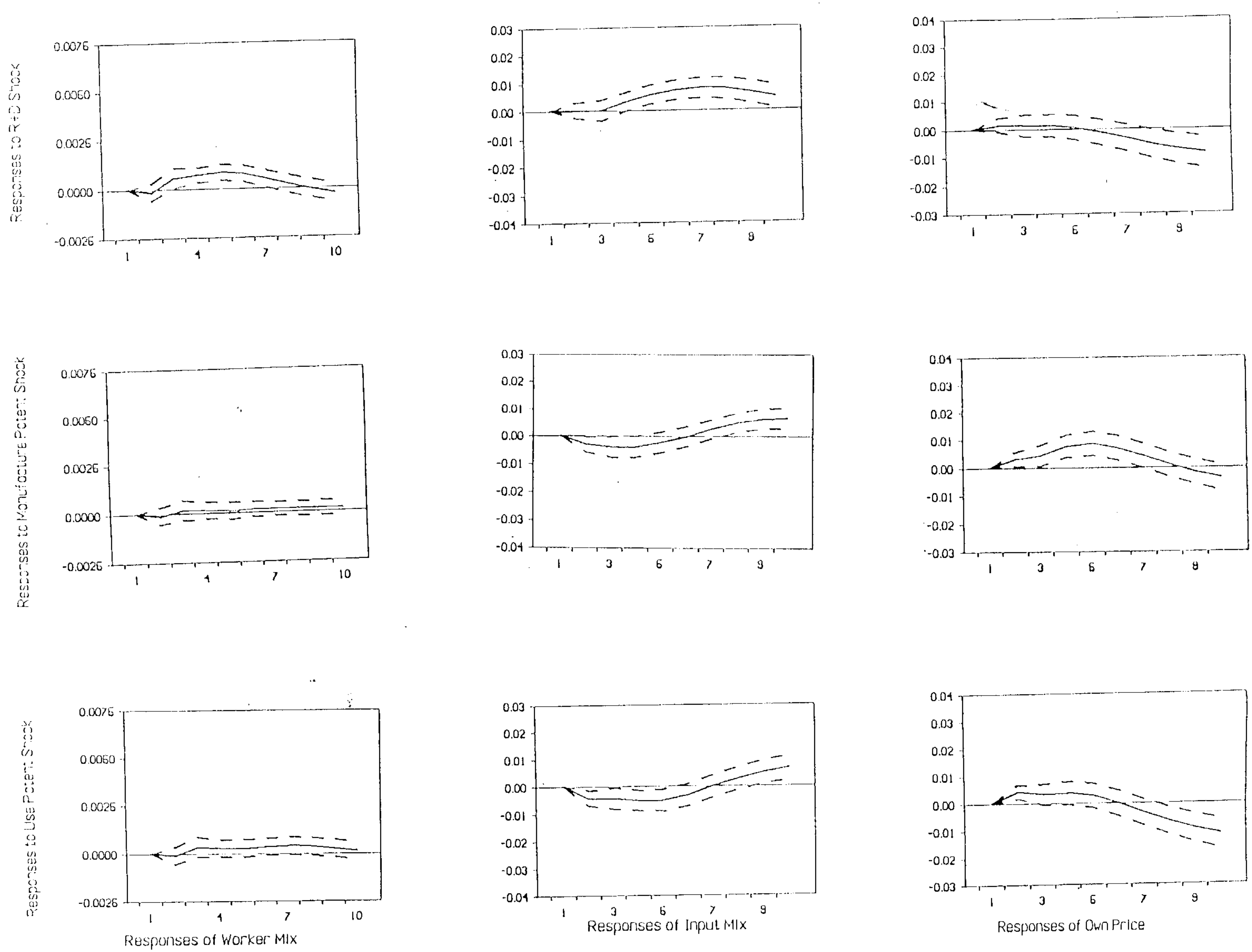

FIGURE 9: Worker Mix, Input Mix, Own Price and Upstream Technology

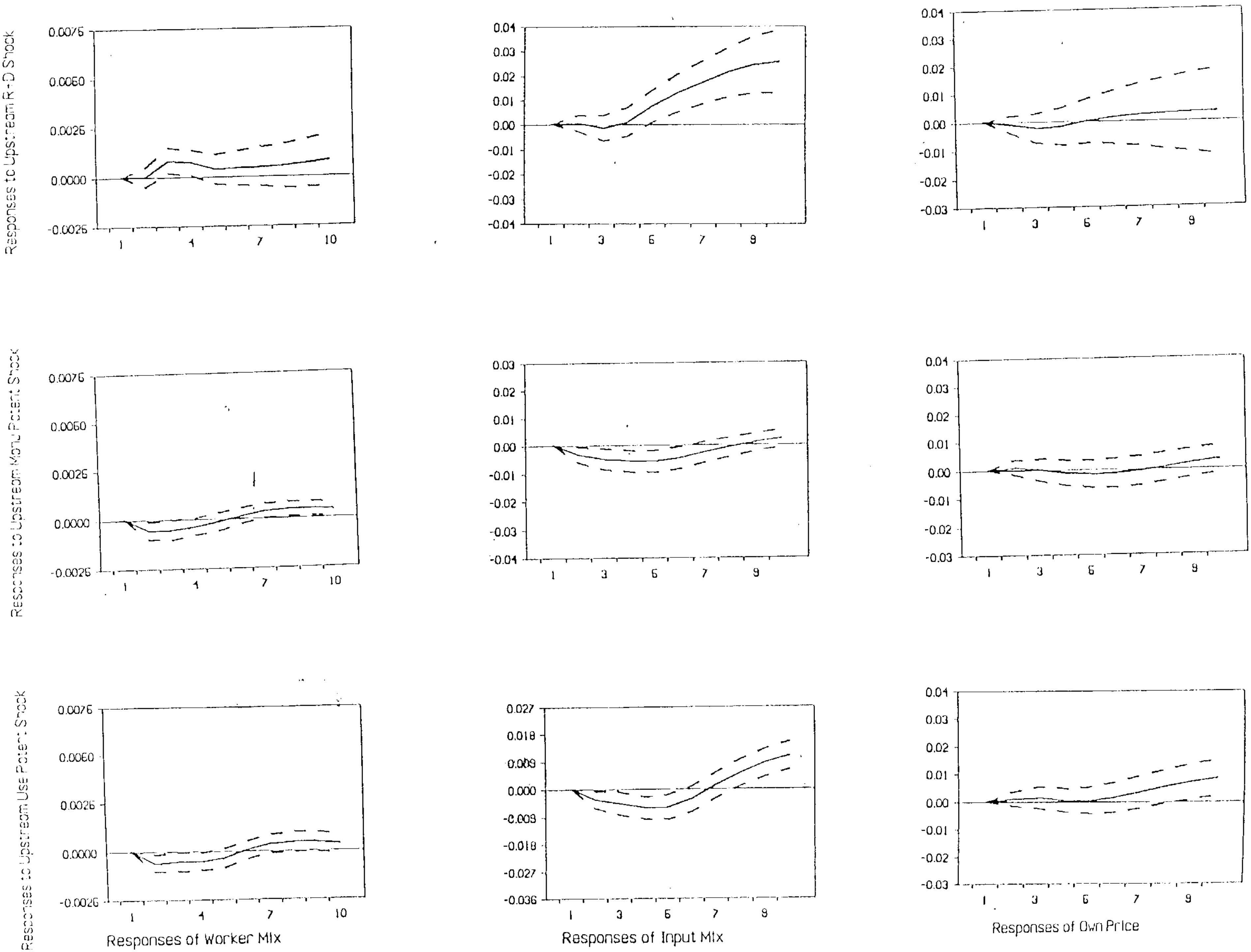

FIGURE 10: Inputs, TFP and Upstream Technology in Nonmanufacturing

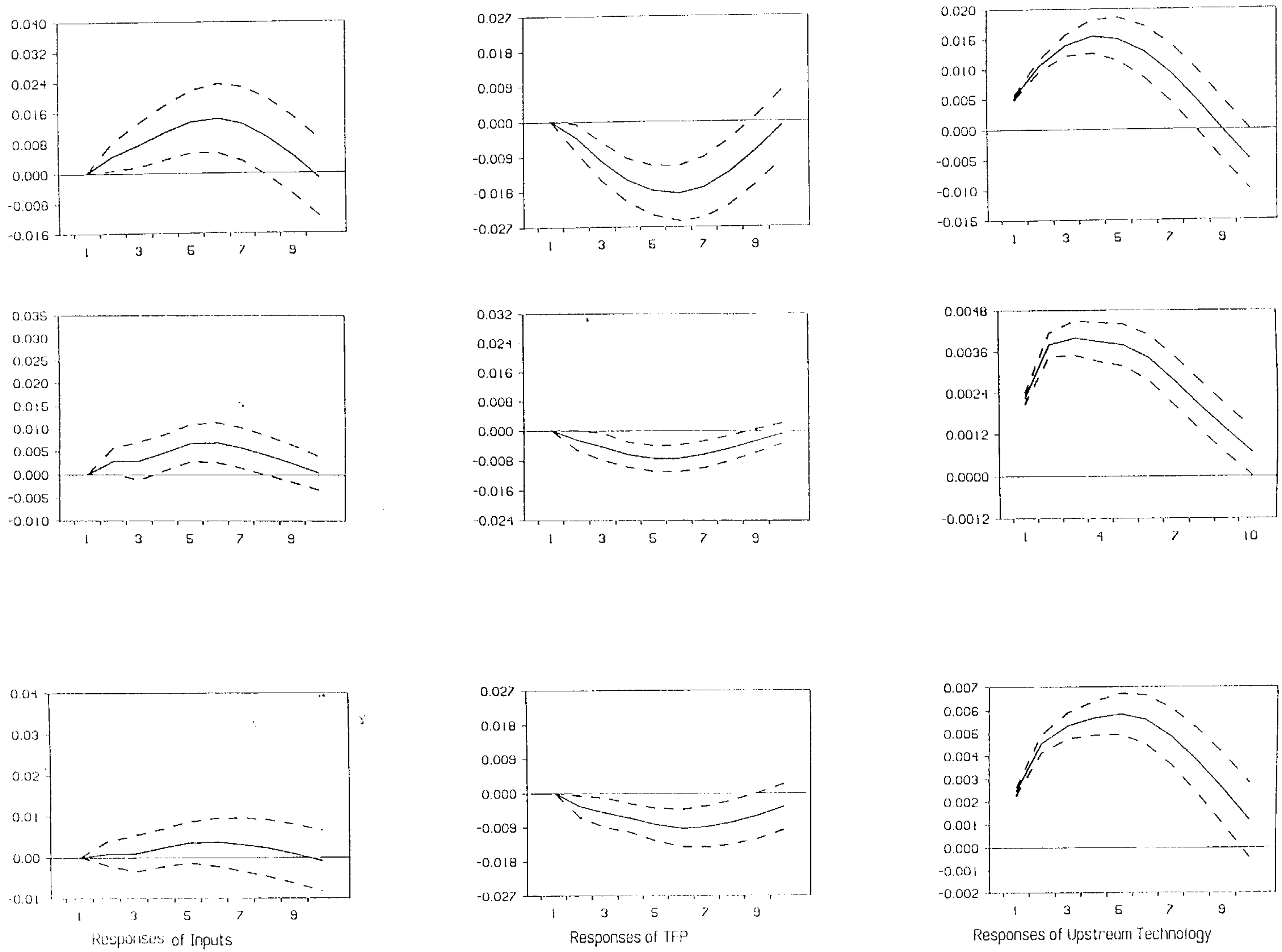

FIGURE 11: K, L, M and Upstream Technology in Nonmanufacturing

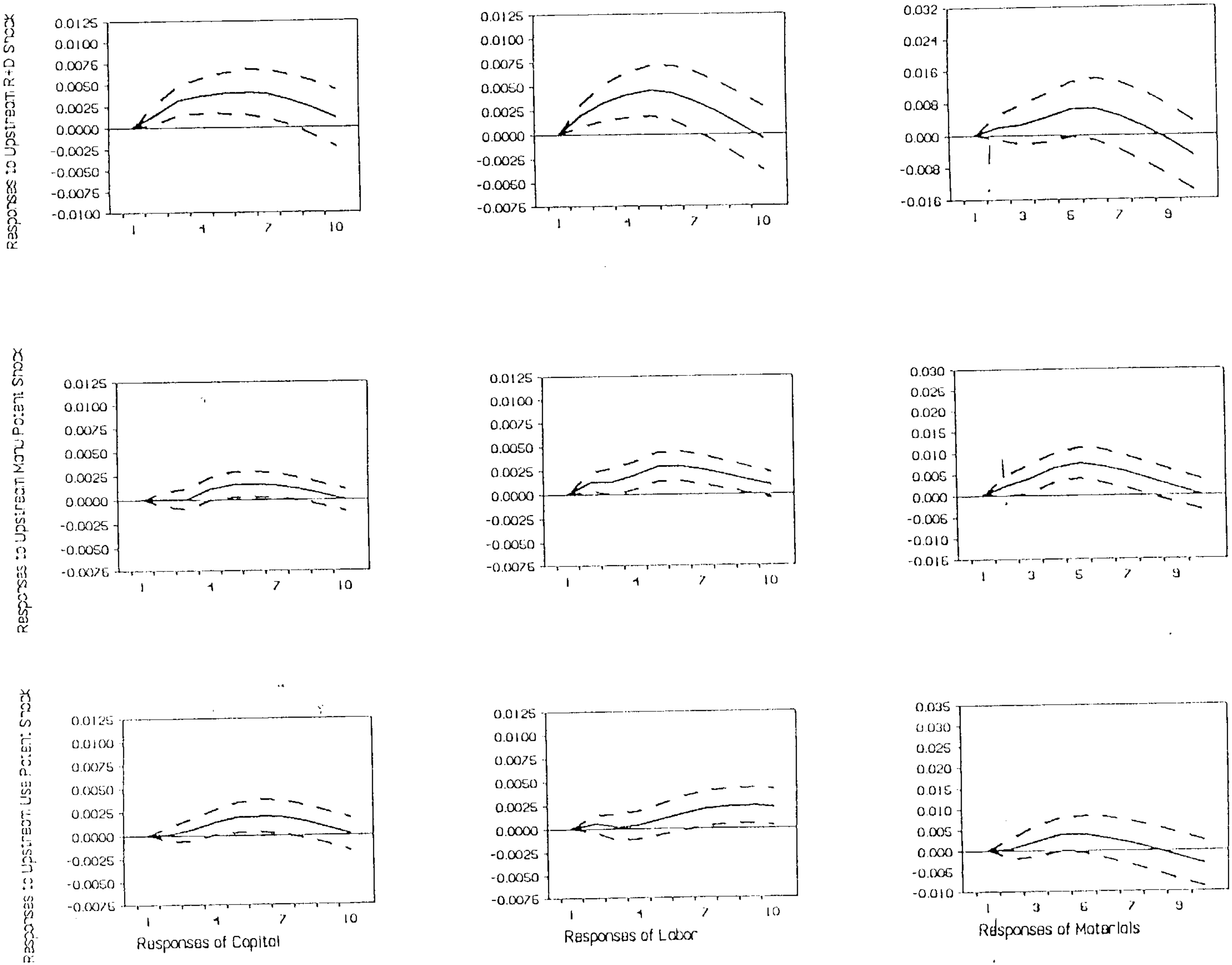

FIGURE 12: Own Technology Shocks in Process-Innovating Industries

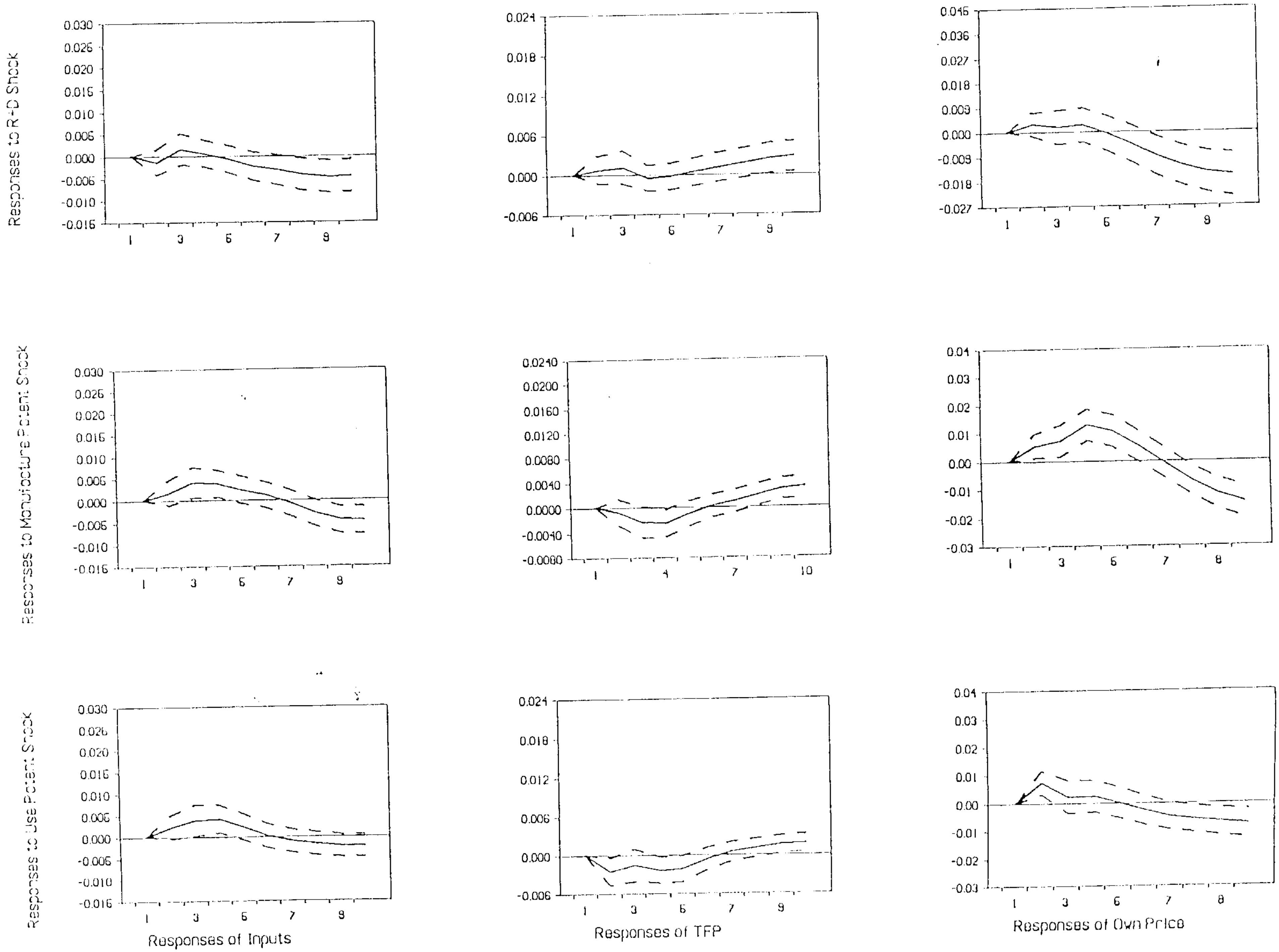

FIGURE 13: Own Technology Shocks in Product-Innovating Industries