

On the Employment Effect of Technology: Evidence from US Manufacturing for 1958-1996 *

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Abstract

Recently, Galí and others find that technological progress may be contractionary: a favorable technology shock reduces hours worked in the short run. We ask whether this observation is robust in disaggregate data. According to our VAR analysis of 458 four-digit U.S. manufacturing industries for 1958-1996, some industries do exhibit temporary reduction in hours in response to a permanent increase in TFP. However, there are far more industries in which technological progress significantly increases hours. Using micro data on average price duration, we ask whether the difference across industries is related to the stickiness of industry-output prices. Among 87 manufacturing goods, we do not find such a relation.

Keywords: Technology Shocks, Hours Fluctuations, Sticky Prices

JEL Classifications: E24, E32

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1 Introduction

Despite controversies regarding its quantitative importance as a source of business-cycle fluctuations, the employment effect of technology is conventionally viewed as expansionary; technological progress not only expands the production frontier but also creates jobs.

Recently, however, a number of studies—initiated by Galí (1999), Basu, Fernald, and Kimball (1998), and Kiley (1998) and reinvestigated by Francis and Ramey (2002)—report that favorable technology shocks may reduce total hours worked in the short run. This is an important finding because, if confirmed, the fluctuation induced by technological progress may violate a simple fact of the business cycle—the co-movement of output and employment, documented at least since Burns and Mitchell (1946).¹

In this paper, we investigate whether this observation is robust at a more disaggregate level. According to our VAR analysis of 458 four-digit U.S. manufacturing industries for 1958-1996, some industries exhibit a decrease in hours worked in response to a favorable technology shock, identified by a stochastic trend component of total factor productivity (TFP). However, there are far more industries in which a permanent increase in TFP leads to a significant increase in both employment and hours per worker in the short run. Among 458 four-digit industries, 148 industries exhibit a statistically significant increased hours of work in response to a favorable technology shock, whereas only 13 industries exhibit significant decreases in hours worked in the short run.

¹In Galí as well as in Kiley, and Francis and Ramey, a technology shock is identified by a stochastic trend of labor productivity from a structural VAR. Basu et al. construct a measure of technology change from production functions, controlling for imperfect competition, utilization, and aggregation effects. In contrast, Shea (1998), distinctive for his use of a direct measure of technology, finds that an increase in the orthogonal components of R&D and patents tends to increase input use, especially labor, in the short run, but to reduce inputs in the long run.

Our results differ from Kiley's, which shows that employment decreases in response to a permanent increase in labor productivity in most two-digit manufacturing industries for 1968:II-1995:IV. However, we do not view these findings necessarily conflicting. We find that the stochastic trends of TFP and labor productivity capture different types of changes in production because labor productivity reflects changes in input mix as well as improved efficiency. For instance, disturbances affecting material-labor or capital-labor ratios (e.g., persistent movement of relative input price changes or trends in sectoral labor supply) generate a negative correlation between labor productivity and hours along the downward sloping marginal product of labor whereas such changes alone do not affect the TFP.

As the contractionary effect of technology is incompatible with a baseline equilibrium model, alternative models have been proposed. Our analysis sheds light on two alternative hypotheses: sticky prices (Galí, Kiley, and Basu et al.) and labor-saving technological progress (Francis and Ramey). Intuitively speaking, if prices do not fall, demand remains unchanged and firms need less input due to the improved technology.² We test this hypothesis by asking whether the cross-sectional difference in an industry's hours response (to a technology shock from the VAR) can be accounted for by the stickiness of industry-output prices (average duration of prices) constructed by Bils and Klenow (2002). For 87 manufacturing goods, which we are able to match with the employment and TFP in the *NBER Database*, we do not find a systematic correlation between the industry's hours response and the average duration of product price.

²Dotsey (1999) and Galí made it clear that the hours response depends on the nature of monetary policy as well as on the price stickiness. For example, hours can increase even under the sticky price if monetary authority is very accommodative to technology shocks. According to Galí, López-Salido and Vallés (2002), the employment effect of technology varies across monetary policy regimes in the U.S.; the negative correlation between hours and technology has weakened since the Volcker-Greenspan era.

Francis and Ramey illustrate that under a strong complementarity between capital and labor, demand for labor input may decrease in the short run in the face of labor-saving technological progress. On one hand, we find that the labor share has indeed decreased significantly in manufacturing in the past four decades (from .57 in 1958 to .38 in 1996) suggesting a presence of labor-saving technological change in manufacturing. On the other hand, our data suggests that under a strong complementarity (e.g., substitution elasticity between capital and labor as low as .5), the decline of labor shares may be accounted for by the relatively slow accumulation of capital in manufacturing as the measured capital-effective labor ratios had decreased by almost 50 percent during the sample period.

The paper is organized as follows. In Section 2, we briefly describe our empirical method, including the VAR and data, and report the estimates on the technology effect on hours. In Section 3, we compare the stochastic trends of TFP and labor productivity, providing a reconciliation with previous studies. In Section 4, we relate our results to the two hypotheses that allow for a negative response of hours to technology. Section 5 provides caveats on our analysis. Section 6 is the conclusion.

2 Evidence from Industry TFP and Hours

2.1 Identifying Technology Shocks

Following the tradition of Blanchard and Quah (1989) and earlier works (e.g., Galí, Kiley), technology shocks are identified by a structural VAR of productivity, x_t , and hours, n_t . Fluctuations of industry productivity and hours are driven by two fundamental disturbances—technology and non-technology shocks—which are orthogonal to each other. Only technology shocks can have a permanent effect on the level of industry productivity. Both technology and non-technology shocks

can have a permanent effect on industry hours. We do not attempt to provide an interpretation of non-technology shocks, which can be either aggregate (e.g., monetary shocks) or sectoral (e.g., reallocation shocks).³

We assume that the vector $[\Delta x_t, \Delta n_t]'$ can be expressed as a (possibly infinite) distributed lag of both types of disturbances:

$$\begin{bmatrix} \Delta x_t \\ \Delta n_t \end{bmatrix} = \begin{bmatrix} C^{11}(L) & C^{12}(L) \\ C^{21}(L) & C^{22}(L) \end{bmatrix} \begin{bmatrix} \varepsilon_t^x \\ \varepsilon_t^n \end{bmatrix} = C(L)\varepsilon_t, \quad (1)$$

where ε_t^x and ε_t^n denote, respectively, the sequence of technology and non-technology shocks. The orthogonality assumption (combined with a standard normalization) implies $E\varepsilon_t\varepsilon_t' = I$. Our identifying restriction corresponds to $C^{12}(1) = 0$. The specification (1) is based on the assumption that industry hours and productivity are integrated of order one, which holds in most manufacturing industries. Note that we do not impose a stationarity of hours (often adopted at the aggregate level based on the balanced-growth path assumption). We also consider an alternative measure which is stationary: the de-trended average workweek of production workers of the industry. In this case, we estimate an analogous model for $[\Delta x_t, \hat{n}_t]'$, where \hat{n}_t denotes deviations of weekly hours from a linear time trend. The main conclusion of the paper is not affected by the choice of hours.⁴

2.2 Data

Industry productivity and hours from the *NBER Manufacturing Productivity Database* (Bartlesman and Gray, 1996) are used to estimate (1). They include 459 four-digit manufacturing industry data for 1958-1996 and largely reflect information in the *Annual Surveys of Manufacturing*. For

³One class of models that is potentially inconsistent with our identifying restriction is endogenous growth models in which non-technology shocks affect the level of technology in the long run.

⁴Altig, Christiano, Eichenbaum and Linde (2002) and Vigfusson (2002) suggest that a strong negative response of hours might be due to omitted variables in a VAR and/or over-differencing of hours.

productivity, we use the measure of TFP growth contained in the *Database* (again see Bartlesman and Gray), which is based on measuring separate factor inputs for non-energy materials, energy, labor, and capital. For TFP higher than four-digit industries, we aggregate four-digit data weighting by the industry’s value-added.

Industry output reflects the value of shipment divided by the price deflator of industry output.⁵ For hours worked, we use total hours employed in the industry, measured by the sum of hours of production and non-production workers. There are no data on workweeks for non-production workers. We follow the *NBER Database*’s convention of setting the workweek for non-production workers equal to 40. We obtain a similar result when we assume that hours of non-production workers are perfectly correlated with those of production workers. The *NBER Database* only includes the wage and salary costs of labor. In calculating the industry labor share, we magnify wages and salary payments to reflect the importance of fringe payments and employer FICA payments in its corresponding two-digit manufacturing industry. The ratio of these other labor payments to wages and salaries in two-digit industries, in turn, is based on information in the *National Income Product Accounts*. Material expenditure includes expenditure on energy as well as on non-energy materials. The capital’s share is calculated as a residual from labor and material share following the *Database*’s convention.⁶ Finally, we use 458 industry data excluding “Asbestos Product” industry (SIC 3292) due to termination of time series in 1993.

All VARs have a lag of one year. While our data are annual, in many industries, we maintain nearly as many observations in quarterly data by constructing a panel. For example, in the estimation of the three-digit “men’s and boy’s furnishing and clothing” industry (SIC 232), we construct

⁵Including or excluding inventory changes in output does not affect the estimates in any significant way.

⁶This implicitly assumes a constant returns to scale production technology, a reasonable approximation of U.S. manufacturing, according to Basu and Fernald (1997) and Burnside, Eichenbaum, and Rebelo (1995).

a panel by stacking six four-digit sub industry data (SIC 2321, 2322, 2323, 2325, 2326, 2329). Likewise, for the panel estimation of a two-digit industry VAR, three-digit industry data are used; for the panel estimation of aggregate manufacturing, durables, and nondurables, two-digit data are used. When a VAR is estimated by panel data, industry dummies are included to allow for different average growth rates of TFP and hours across sub-industries. We also report the estimates based on the aggregated time-series data. The results do not change significantly. Standard errors are computed by bootstrapping 500 draws.

2.3 Results

Figure 1 displays the responses of TFP and hours for the aggregate manufacturing industry. In response to a one-standard-deviation technology shock (which eventually increases the manufacturing TFP by 2.8 percent), hours worked increases by .7 percent at impact. Hours continues to rise for two years until it reaches the new steady state, 1.7 percent higher than before. In response to a non-technology shock, the manufacturing industry experiences a temporary increase of TFP, suggesting a pro-cyclical factor utilization. Hours worked increases and remains high. We obtain similar results with stationary hours, the (linearly de-trended) average workweek of production workers. The average workweek increases in the short run in response to both technology and non-technology shocks.

While we find similar responses for durables and nondurables, the hours response varies vastly across industries. For example, in “Transportation Equipment,” hours increases almost by 7 percent in response to a technology shock which increases the TFP by 4 percent in the long run; whereas hours falls and persistently remains low in response to a technology shock in “Agricultural Chemicals” (Figure 2).

Table 1 lists both unconditional and conditional correlations between the growth rates of hours and TFP for two-digit industries.⁷ For aggregate manufacturing, the unconditional correlation between TFP and hours is .39 (with standard error of .05). The correlation conditional on technology shocks is .72 (.22); the manufacturing industry tends to hire more labor when there is technological progress. The conditional correlation on non-technology shocks is also significantly positive, .73 (.03); a temporary increase in TFP is associated with longer hours of work.

The correlation conditional on technology varies across two-digit industries. Among those statistically significant, it ranges from -.79 (.46) in “Lumber and Wood Products except Furniture” to .99 (.02) in “Tobacco Products.” Yet the majority of two-digit manufacturing industries show positive correlations between TFP and hours conditional on technology shocks; 12 industries exhibit .7 or higher. Among those statistically significant at 10 percent, 14 industries exhibit a positive correlation conditional on technology whereas only two industries exhibit a negative conditional correlation. This pattern is robust across the level of aggregation. Among four-digit industries, 233 exhibit statistically significant positive correlations conditional on technology whereas only 30 industries show negative correlations conditional on technology shocks.

The conditional correlation reflects the overall response of hours to a technology shock. As our primary interest is in the short-run response, in Table 2 we summarize the number of industries with positive and negative contemporaneous response of hours to technology from the bi-variate industry VARs. The numbers in parentheses represent the cases that are statistically significant at

⁷Following Galí, we compute the conditional correlation on technology based on VAR estimates. Given an estimate for $C(L)$, estimates of conditional correlations are obtained as:

$$cor(\Delta x_t, \Delta n_t | \varepsilon^i) = \frac{\sum_{j=0}^{\infty} C_j^{1i} C_j^{2i}}{\sqrt{var(\Delta x_t | \varepsilon^i) \times var(\Delta n_t | \varepsilon^i)}}$$

for $i = x, n$, where $var(\Delta x_t | \varepsilon^i) = \sum_{j=0}^{\infty} (C_j^{1i})^2$ and $var(\Delta n_t | \varepsilon^i) = \sum_{j=0}^{\infty} (C_j^{2i})^2$.

10 percent. Looking at the first row, the two-digit industry panel-data estimates, 4 industries exhibit negative responses (only one of them is statistically significant at 10 percent), whereas 16 industries show positive responses (8 of them significant). The result is similar when the aggregated (non-panel) data are used. There are 14 positive and 6 negative responses. For three-digit industry panel-data estimates, 115 (53 significant) industries show a positive response and 25 (3 significant) show a negative response. Within the full sample of the 458 four-digit industries, 343 (148 significant) industries show a positive response, whereas 115 industries (13 significant) show a negative response. Despite considerable heterogeneity across sectors, the employment effect of technology does not appear strongly inconsistent with the equilibrium view: technological progress tends to increase the demand for labor. However, its quantitative importance for the cyclical variation of hours (in terms of the forecast error variances from the VAR) is small: technology shocks account for less than 20 percent of two-year volatility of hours growth in manufacturing.⁸

3 TFP vs. Labor Productivity

Our result—hours worked increases in response to a trend component of TFP—appears at odds with Kiley’s, which shows that the technology-driven components of labor productivity and employment are negatively correlated for 15 of the 17 two-digit manufacturing industries for 1968:II-1995:IV. However, we do not see our results as necessarily in conflict with Kiley’s. In Kiley as well as in Galí technology shocks are identified by the stochastic trends of labor productivity. In fact, when we use labor productivity (instead of TFP), we also find a strong negative response in hours in most industries, consistent with Kiley.

⁸This is a common result in structural VARs with long-run identification such as Blanchard and Quah based on aggregate unemployment and output.

In this section, we provide an explanation for this difference by showing that the stochastic trends of labor productivity and TFP reflect different types of changes in production process over time. Figure 3 exhibits TFP, labor productivity (value-added divided by total hours), and total hours worked in manufacturing for 1958-1996. While both TFP and labor productivity show positive trends, the magnitudes are somewhat different. To illustrate, suppose the labor-augmenting technology, denoted by X_t , grows at rate g . If the balanced growth property were held, output, capital, and labor productivity would grow at rate g and the measured TFP, Z_t , would grow at rate αg , where α is labor share. Given the average labor share of .5 in manufacturing during the sample period, the labor productivity should have grown twice as fast as the measured TFP to be consistent with the balanced growth path. Yet in the last 40 years, TFP has doubled and labor productivity has tripled. In other words, the balanced growth path predicts that the capital-effective labor ratio ($\frac{K_t}{N_t X_t}$) is stationary. However, this ratio has decreased significantly (almost by 50 percent) in aggregate manufacturing from 1958 to 1996.

The difference between the two productivity measures is dramatic in some industries. In “Leather and Leather Products” no trend appears in the TFP shown in Figure 4, whereas labor productivity exhibits a strong trend caused by a continuous decrease in employed hours over time. For aggregate manufacturing, we could not reject the null-hypothesis of no co-integration between TFP and labor productivity at 10 percent significance level. The null-hypothesis of no co-integration is not rejected at 10 percent for 17 of the 20 two-digit manufacturing industries.

Consider a production function $Y_t = F(N_t, K_t, M_t; Z_t)$ where Y_t, N_t, K_t, M_t , and Z_t denote output, labor, capital, material, and TFP, respectively. With lowercase letters for logged values, the growth rate of labor productivity $\Delta(y_t - n_t)$ is:

$$\Delta(y_t - n_t) \simeq \Delta z_t + (\alpha_{n,t} - 1)\Delta n_t + \alpha_{k,t}\Delta k_t + \alpha_{m,t}\Delta m_t, \quad (2)$$

where $\alpha_{n,t}$ denotes output elasticity of labor, and so forth. These elasticities, measured by the average revenue shares at time t and $t - 1$, are allowed to vary over time to accommodate a factor-biased technological progress.

Given the technology, as hours increases the labor productivity decreases along the downward sloping marginal product of labor ($\alpha_n < 1$). In general, labor productivity growth can reflect improved technology, decreased hours of work, or increased use of other inputs. Thus, changes in material-labor and capital-labor ratios due to shifts in input prices affect labor productivity, whereas such changes alone will not affect the TFP.

In order to understand the extent to which input growth accounts for labor productivity growth, we decompose the stochastic trend of labor productivity into the input growth and TFP growth based on (2). We first expand the VAR to include other inputs such as capital and material: $[\Delta x_t, \Delta n_t, \Delta k_t, \Delta m_t]' = C(L)\varepsilon_t$. We impose a similar identifying restriction in which only technology shocks affect productivity x in the long run: $C^{12}(1) = C^{13}(1) = C^{14}(1) = 0$. Two sets of estimates for $C(L)$ are obtained, respectively, with TFP (denoted by Model A) and labor productivity (denoted by Model B) as a measure of productivity x . We do not attempt to identify other shocks as it would require further (probably controversial) restrictions. The contribution of input growth on labor productivity is calculated based on its long-run multiplier from the VAR and output elasticity (measured by average revenue share); specifically, $(\alpha_n - 1)C^{12}(1)$, $\alpha_k C^{13}(1)$, and $\alpha_m C^{14}(1)$, respectively, for labor, capital, and material.

According to Model A (in which technological progress is identified by the permanent components of TFP) in Table 3, a permanent TFP shock increases the labor productivity by a similar magnitude in the long run, as the contributions of inputs on labor productivity tend to offset each other. For aggregate manufacturing, a 2.76 percent increase (caused by a one-standard-deviation

shock from the VAR) of labor productivity is decomposed into -.51 percentage points due to an increased hours of work $((\alpha_n - 1)\Delta n)$, -.26 due to a decreased capital $(\alpha_k\Delta k)$, .77 due to an increased material $(\alpha_m\Delta m)$, and 2.76 due to an improvement in TFP (ΔTFP) . A similar pattern is found across two-digit industries; the labor productivity and TFP grow in a similar magnitude in the long run.

By contrast, when labor productivity is used (Model B) to identify technology, a significant portion of labor productivity is explained by an input growth. For aggregate manufacturing, a 4 percent increase in output per hours (caused by a one-standard deviation shock from the VAR) consists of 2.44 percentage points due to an increase in TFP, .28 due to decreased hours, -.08 due to decreased capital, and 1.36 due to increased material. In nondurables, hours plays a more important role. For a 3.25 percent increase of labor productivity, a 1.49 percentage point increase is due to increased TFP and a .79 percentage point increase is due to decreased hours. Overall, about half of the trend in labor-productivity is accounted for by the input growth in manufacturing.

4 Implications for Two Alternative Hypotheses

The industry VAR analysis reveals a considerable heterogeneity across sectors in the hours response to technology. A negative response, in particular, is apparently inconsistent with the prediction of the baseline (flexible-price) equilibrium model. Alternative models have been proposed to allow for a negative response of hours to technological progress. In this section we document some facts that provide implications for two alternative hypotheses: sticky prices (Galí, Kiley, and Basu et al.) and labor-saving technological progress (Francis and Ramey).⁹

⁹Also, Jermann (1998) shows that a combination of habit formation in consumption and adjustment cost in investment can generate a negative response of hours to a favorable technology shock.

4.1 Sticky Prices

Intuitively speaking, when price is fixed, the demand for goods remains unchanged and firms need fewer inputs, including labor, to produce the same amount of output thanks to the improved TFP. We test this hypothesis by asking whether the industry response of hours (to technology shocks) from a VAR is systematically correlated with the stickiness of industry-output price.

We take advantage of the recent micro data constructed by Bils and Klenow (2002), who compute the average monthly price-change frequency for 350 goods and services from unpublished data on the price quotes collected by the BLS for 1995-1997. We exploit the cross-sectional variation in these measures. For 87 manufacturing goods, we are able to match the SIC industry classification with the ELIs.¹⁰ In matching the two data sets, each ELI corresponds to a four-digit SIC industry for 44 goods. For 11 goods, one ELI item corresponds to multiple four-digit SIC industries. In this case, we aggregate TFP (weighted by value-added output) and hours of the industries. For 32 goods, multiple ELIs belong to one three- or four-digit SIC industry. In this case, the CPI weights from the BLS are used to calculate the average price-change frequency of the goods. The average duration of price (the inverse of average price-change frequency) for 87 goods is 3.4 months. Gasoline is at the flexible end of the spectrum with an average duration of 0.8 months; newspapers are at the sticky end with an average duration of 29.9 months.

In Figure 5, we plot the short run response of hours to a technology shock against the (log) average monthly duration of prices for 87 manufacturing goods. The short run response refers to the contemporaneous effect on hours of a technology shock that increases the industry TFP by one

¹⁰To calculate the CPI, the BLS collects prices for about 71,000 non-housing goods and services per month. These are collected from around 22,000 outlets across 44 geographic areas. The BLS divides non-housing consumption into roughly 350 categories called “entry-level items” (ELIs).

percent in the long run. Under the sticky-price hypothesis we expect a negative correlation between the hours response and average price duration. However, no systematic relationship appears; the cross-sectional correlation between the hours responses and average duration of prices is .02. We repeat the same plot (the right panel), now with y-axis representing the hours response to a shock that increases the labor productivity by one percent in the long run (based on VARs of hours and labor productivity). Again, we do not find a systematic relation between the hours response and average duration of price.

Our evidence—a near zero correlation between price duration and the VAR statistics—does not reject a potential role of sticky price for the propagation mechanism of business-cycle fluctuations. However, it suggests that price stickiness may not be a primary reason for firms’ use of labor input differently across industries in the face of permanent changes in technology.¹¹

4.2 Labor-Saving Technological Progress

Technological changes often accompany substitution of inputs in production (e.g., factor-biased technological progress). Francis and Ramey show that labor-saving technological progress may decrease hours worked under a strong complementarity between capital and labor. Consider a CES production function that nests Francis and Ramey:

$$\tilde{Y}_t = \left[\alpha_t (X_t N_t)^{1-\frac{1}{\sigma}} + (1 - \alpha_t) K_t^{1-\frac{1}{\sigma}} \right]^{\frac{\sigma}{\sigma-1}}. \quad (3)$$

Here \tilde{Y}_t denotes the value-added output, X_t , a labor-augmenting technological progress, and σ the substitution elasticity between capital and labor. In Francis and Ramey, the production technol-

¹¹Carlsson (2000) and Marchetti and Nucci (2001) provide evidence supporting the sticky price hypothesis based on, respectively, Swedish and Italian manufacturing data. Both studies use a method similar to Basu et al. to identify the technology and find that a negative response of hours to a technology shock is more pronounced in sectors with stickier prices. We discuss the method of Basu et al. in Section 5.

ogy is a Leontief ($\sigma = 0$) and the labor-saving technological progress refers to an increase in X_t associated with a decrease in α_t . The first order conditions of a firm's cost minimization imply:

$$\frac{W_t N_t}{R_t K_t} = \frac{\alpha_t}{1 - \alpha_t} \left(\frac{K_t}{N_t X_t} \right)^{\frac{1}{\sigma} - 1}, \quad (4)$$

where W_t and R_t denote wage rate and rental rate for capital. The factor-share ratio ($\frac{W_t N_t}{R_t K_t}$) reflects the output-input elasticity ($\frac{\alpha_t}{1 - \alpha_t}$) and the capital-effective labor ratios ($\frac{K_t}{N_t X_t}$). If the production function is a Cobb-Douglas ($\sigma = 1$), capital-labor ratio has no impact on factor shares; the labor share simply reflects a technological change in α . However, when capital and labor are complements ($\sigma < 1$), a decrease in capital-effective labor ratio decreases the labor share relative to capital.

We note two observations in manufacturing in the last four decades. First, the labor share (in value-added) has significantly decreased in manufacturing (from .57 in 1958 to .39 in 1996). Second, the capital-labor ratio has not kept up with the measured TFP. Given the time series of factor shares, capital-labor ratios, and X_t (based on the TFP in Section 2), one can compute the implied values of α_t over time that satisfy the equation (4).¹² Figure 6 shows the implied time series of α_t , respectively, with σ of 2/3, 1, and 1.5 for aggregate manufacturing. This range of σ includes the empirically plausible values for U.S. manufacturing (Lucas, 1969; Berndt, 1976).

The implied values of α_t has indeed decreased over time, supporting the mechanism proposed by Francis and Ramey. Even when capital and labor exhibit a fairly low degree of substitutability ($\sigma = 2/3$), almost half of the decline of labor shares are attributed to the decrease of α_t . However, a too strong complementarity (such as Leontief) may rule out the role of α_t in the downward trend of labor shares because the capital-labor ratio has not grown as fast as the labor-augmenting

¹²The measured TFP is adjusted by the (two-period average) labor shares to be consistent with the equation (3): $\alpha_t X_t = TFP_t$.

productivity in manufacturing. (Recall (3).) For example, when $\sigma = .5$, the observed decline of labor share is consistent with a constant α because $\frac{K_t}{N_t X_t}$ has decreased by almost 50 percent during the sample period.

5 Some Caveats

Shea and Basu et al. investigate the employment effect of technology with disaggregate data. Both studies use industry TFP as we do, but draw somewhat different results; Basu et al. find a negative correlation between technology and inputs, especially for labor; Shea finds hours increases in the short run but decreases in the long run. We briefly describe the methodological differences here.

We share the concern of Shea and Basu et al. that the measured TFP contains cyclical components such as factor utilization. In Basu et al., TFP is corrected for both capital utilization and labor effort. Despite their careful analysis, this method is potentially vulnerable to a possible spurious negative correlation between the corrected TFP and hours, the variable used to approximate the utilization rate. (See Bils [1998] for detailed discussion on this.) Shea takes a unique approach by making use of direct measures such as R&D and patents. However, confronted with an identification problem in a VAR, he imposes a restriction on the contemporaneous effects. The technology variable is placed last in a VAR: industry R&D is allowed to respond to the business cycle but not vice versa. We rely on a long-run restriction on the times series of TFP assuming that intensity of factor utilization has no trend during the sample period.

We provide three caveats on our empirical analysis. First, TFP in the *NBER Database* is constructed under two assumptions: the price-cost markup of 1 and constant returns to scale technology. While they are reasonable approximations of U.S. manufacturing (e.g., Basu and Fernald, and Burnside et al.), input growth and TFP growth may be spuriously correlated if the

true markup is higher than 1 (Hall, 1987).¹³ Suppose the growth rate of the “true” TFP is Δz_t^* and the markup is μ . The measured TFP growth (*incorrectly* assuming a markup of 1) is:

$$\Delta z_t = \Delta z_t^* + (\mu - 1)(\alpha_m \Delta m_t + \alpha_n \Delta n_t + \alpha_k \Delta k_t). \quad (5)$$

If the actual markup is above 1, the measured TFP is spuriously correlated with inputs. In Table 4, we re-estimate the bi-variate VAR of hours and TFP adjusted for the markup of 1.1 and 1.2 based on (5). With the markup ratio of 1.1, the result remains the same: technology shocks tend to increase hours worked in the short-run. When the markup is 1.2, fairly high given the small profit rates in manufacturing, a permanent increase in TFP now has a negative impact on hours in the short run and virtually no effect on hours in the long run. However, we are concerned that too high a markup may generate a spurious negative correlation between the corrected TFP and inputs.

Second, our analysis is based on the gross output. The contribution of material input does not appear in the net output measure such as value added. When the value added measures are used, the stochastic trends in TFP and labor productivity do not diverge so much as in the gross output measure.¹⁴ Nevertheless, dissimilarity between the two measures persists in manufacturing. In a bi-variate VAR of aggregate manufacturing, hours increases by .32 percent initially and by .85 percent in the long run in response to a one-standard-deviation permanent TFP shock (which eventually increases the TFP by 8.9 percent). The conditional correlation between hours and the permanent component of TFP is .57 (with standard error of .43). By contrast, hours decreases

¹³We thank Jordi Galí for suggesting this exercise.

¹⁴The value-added-based TFP growth of the industry is obtained by $\Delta \tilde{z} = \frac{\Delta z}{1 - \alpha_m}$ as suggested in Basu and Fernald (1999), where Δz is TFP growth based on gross output. This implicitly assumes a Leontief technology between value added output and material input.

by .89 percent initially but increases by .1 percent in the long run in response to a permanent labor productivity shock (which eventually increases the labor productivity by 5.9 percent). The conditional correlation of hours and permanent components of labor productivity is $-.58$ (with standard error of $.22$).

Finally, our data are limited to manufacturing, no longer a major sector of the U.S. economy. When the aggregate (nonfarm business sector) TFP and hours are used, hours worked slightly decreases (statistically not significant) in response to a permanent TFP shock (Table 4). However, as Figure 7 shows, we still see a difference in the hours responses; a permanent labor productivity shock generates a much more pronounced negative response of hours. Given the considerable heterogeneity within manufacturing, it appears that more research on micro and historic data—such as Gort and Klepper (1982), Grilliches and Lichtenberg (1984), Kortum (1993), Shea (1998), and Basu et al. (1999)—are needed to better understand what technology shocks are and what they do.

6 Conclusion

Based on aggregate time series of labor productivity and hours, Galí and many others report that favorable technology shocks may reduce hours worked in the short run, which is apparently incompatible with the baseline equilibrium model. We investigate whether this finding is robust in more disaggregated data.

According to our analysis of 458 U.S. manufacturing industries for 1958-1996, hours response varies vastly across industries. Many industries exhibit reduction in hours in response to a permanent increase in TFP, consistent with earlier studies. However, there are far more industries in which technological progress leads to a significant increase in hours both in the short and long run.

We provide a reconciliation with earlier studies by showing that the stochastic trends of labor productivity and TFP reflect different changes in production in manufacturing as labor productivity reflects changes in input mix as well as improved efficiency.

Our analysis sheds some light on two hypotheses that allow for a negative response of hours to technology: sticky prices and labor-saving technological progress. For 87 manufacturing goods, the cross-sectional correlation between the hours response (to technology) and the measure of price stickiness (average duration of output price) is close to zero. We find that about half of the observed downward trends in labor shares in manufacturing may be due to technological changes in the form of labor saving. While considerable work remains to be done, the employment effect of technology in U.S. manufacturing does not seem strongly inconsistent with the prediction of the equilibrium view.

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Table 1: Correlations between TFP and Hours in Manufacturing for 1958-1996

SIC	Industry	<u>Unconditional</u>	<u>Conditional</u>	
			Technology	Nontechnology
Aggregate Manufacturing		.3953** (.0560)	.7262** (.2218)	0.7238** (0.0320)
Durables		.5026** (.0624)	.7098** (.2114)	.7555** (.0329)
24	Lumber And Wood Products, Except Furniture	.0327 (.0788)	-.7909* (.4696)	.5878** (.1289)
25	Furniture And Fixtures	.5578** (.0585)	.8521** (.0948)	.7661** (.1214)
32	Stone, Clay, Glass, And Concrete Products	.4763** (.0495)	.8958** (.1193)	.7147** (.0316)
33	Primary Metal Industries	.2266** (.0743)	.4518 (.6231)	.7098** (.1288)
34	Fabricated Metal Products	.4474** (.0694)	.9463** (.0538)	-.6360 (.6418)
35	Industrial, Commercial Machinery And Computer Equipment	.5473** (.0525)	.9469** (.0613)	.7462** (.2236)
36	Electronic Equipment, Except Computer Equipment	.4415** (.0714)	.7189* (.3728)	.8238** (.0324)
37	Transportation Equipment	.5198** (.0527)	.9794** (.0186)	-.5694** (.1681)
38	Measuring, Analyzing, And Controlling Instruments	.3599** (.0686)	.8938** (.0899)	-.6201 (.5788)
39	Miscellaneous Manufacturing Industries	.2182** (.0550)	.7012** (.3276)	.6603 (.4319)
Nondurables		.2698** (.0600)	.7094 (.4755)	.7121** (.0936)
20	Food And Kindred Products	-.0142 (.0848)	.1044 (.6851)	-.6404 (.6169)
21	Tobacco Products	.4122** (.0711)	.9989** (.0262)	-.6492 (.5474)
22	Textile Mill Products	.1902** (.0635)	.6293* (.3318)	.6716 (.5362)
23	Apparel And Other Finished Products	.2701** (.0793)	.9006** (.2193)	.6635 (.6507)
26	Paper And Allied Products	.1027 (.1115)	-.9997 (.7403)	.6680** (.2343)
27	Printing, Publishing, And Allied Industries	.2947** (.0749)	.9330** (.3853)	.7086** (.2018)
28	Chemicals And Allied Products	.0656 (.0554)	-.5983** (.2634)	.6281** (.0404)
29	Petroleum Refining And Related Industries	.2672* (.1364)	.9964** (.4957)	.7229 (.6635)
30	Rubber And Miscellaneous Plastics Products	.3128** (.0819)	.8154** (.3047)	.6733 (.4344)
31	Leather And Leather Products	.1264 (.0792)	.3057 (.7011)	.7189** (.3385)

Note: The correlation conditional on technology and non-technology shocks are estimates from the VAR. The numbers in parentheses are standard errors. Those with double asterisks are statistically significant at 5 percent.

Table 2: Short-Run Response of Hours to Technology in Manufacturing for 1958-1996

	Data	Number of Industry	
		Negative	Positive
two-digit	panel	4 (1)	16 (8)
	aggregated	6 (0)	14 (5)
three-digit	panel	25 (3)	115 (53)
	aggregated	36 (7)	104 (42)
four-digit		115 (13)	343 (148)

Note: The number of industries with a positive or negative short run response of hours to a technology from industry VARs of TFP and hours. Those in parentheses are the number of industries whose estimates are statistically significant at 10 percent.

Table 3: Decomposition of Stochastic Trends in Labor Productivity: Percentage Changes

Model A							Model B						
	$\Delta(y-n)$	$(\alpha_n-1)\Delta n$	$\alpha_k\Delta k$	$\alpha_m\Delta m$	ΔTFP		$\Delta(y-n)$	$(\alpha_n-1)\Delta n$	$\alpha_k\Delta k$	$\alpha_m\Delta m$	ΔTFP		
Manufacturing	2.76	-0.51	-0.26	0.77	2.76		4.00	0.28	-0.08	1.36	2.44		
Aggregate													
Durables	2.98	-0.63	-0.07	1.14	2.55		5.03	0.11	0.08	1.30	3.53		
24 :	4.51	0.15	0.06	0.48	3.81		6.15	2.03	0.43	0.66	3.04		
25 :	2.54	-2.73	0.02	2.34	2.91		4.03	-0.76	0.28	2.81	1.71		
32 :	3.13	-1.44	-0.37	1.50	3.44		4.13	0.49	-0.06	1.63	2.06		
33 :	5.38	-0.27	-0.35	0.52	5.48		5.97	0.30	-0.20	2.19	3.66		
34 :	4.39	-3.03	-0.06	3.20	4.28		4.86	-1.81	0.01	3.42	3.24		
35 :	4.75	-1.90	0.12	2.41	4.12		6.78	-0.34	0.02	2.48	4.61		
36 :	6.81	-0.49	-0.00	1.63	5.67		9.36	0.08	0.16	1.91	7.21		
37 :	4.94	-5.15	-0.35	5.91	4.53		5.61	-2.43	-0.39	5.51	2.93		
38 :	4.38	-3.08	0.54	1.91	4.02		4.81	-0.84	0.64	1.98	3.03		
39 :	4.10	-1.08	-0.08	1.00	4.26		5.11	0.44	0.11	1.13	3.42		
Nondurables	2.53	-0.00	-0.45	0.06	2.93		3.25	0.79	-0.23	1.20	1.49		
20 :	1.84	0.25	-0.26	-1.01	2.87		3.57	1.30	0.10	0.93	1.25		
21 :	2.75	-2.58	-1.73	1.60	5.46		6.96	3.35	-0.46	1.48	2.59		
22 :	2.58	-0.92	-0.15	0.44	3.21		4.97	-0.08	0.02	3.38	1.65		
23 :	4.42	-0.48	-0.28	1.23	3.94		6.59	1.96	-0.23	1.79	3.06		
26 :	3.39	0.14	-0.09	-0.52	3.86		4.24	1.66	0.06	-0.84	3.36		
27 :	3.70	-0.86	-0.45	1.11	3.90		4.95	1.11	0.02	0.95	2.88		
28 :	3.83	0.67	-1.13	-0.36	4.65		5.10	1.26	-0.41	0.99	3.27		
29 :	2.79	-1.13	-0.08	-0.46	4.46		6.43	1.26	-0.17	4.20	1.14		
30 :	2.80	-0.51	-0.91	0.79	3.43		4.40	1.66	-0.19	0.91	2.03		
31 :	6.13	-0.76	-1.02	0.55	7.36		8.62	2.49	-0.40	1.07	5.46		

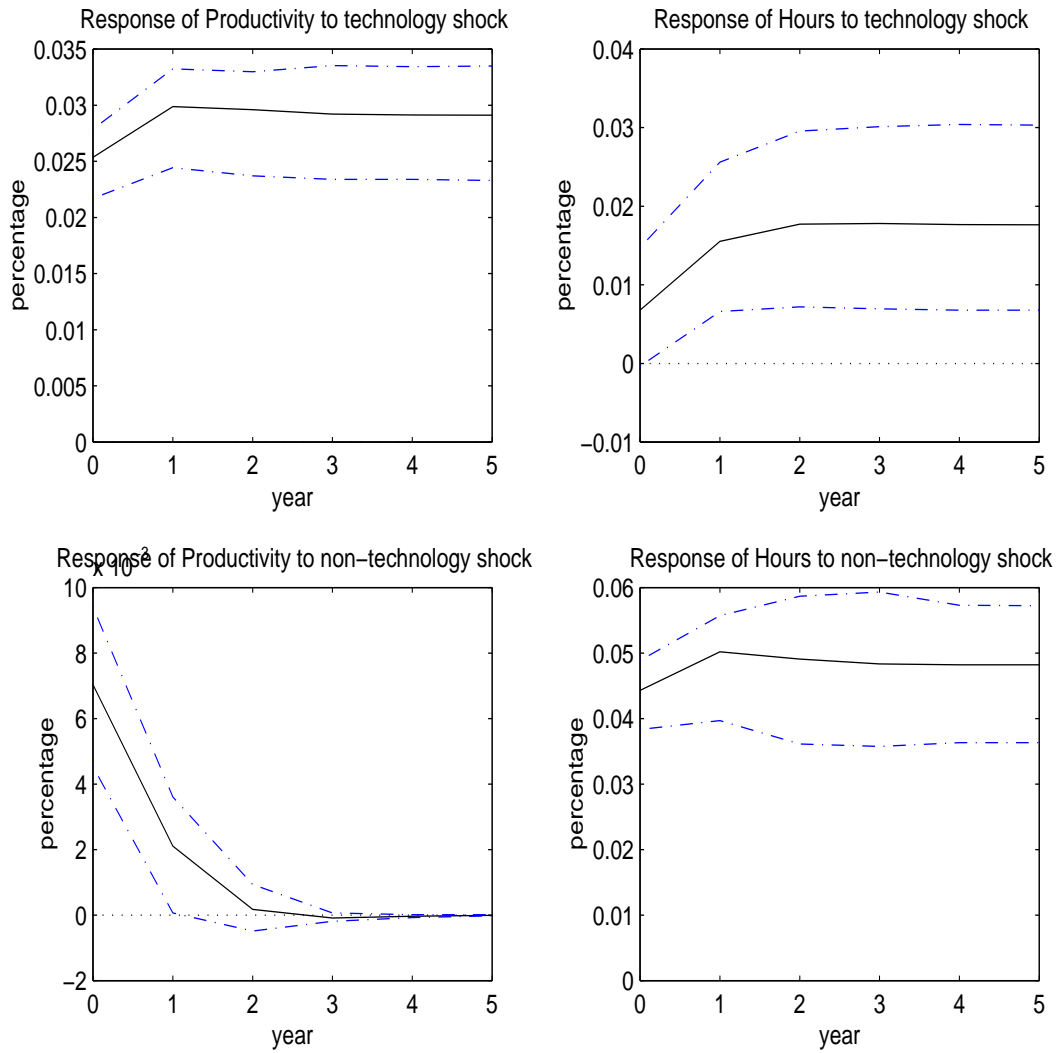
Note: The decomposition is based on equation (2). Model A and Model B identify the technology shock, respectively, from the stochastic trends of TFP and labor productivity.

Table 4: Imperfect Competition, Net Output, and Aggregate Economy

Productivity Measure	<u>Gross Output</u>		<u>Net Output</u>	
	Short Run	Long Run	Short Run	Long Run
TFP ($\mu = 1$)	.0088 (.0065)	.0192** (.0065)	.0062 (.0075)	.0155** (.0071)
TFP ($\mu = 1.1$)	.0055 (.0076)	.0161** (.0078)	.0012 (.0074)	.0109 (.0077)
TFP ($\mu = 1.2$)	.0042 (.0073)	.0111 (.0082)	-.0059 (.0076)	.0034 (.0088)
Labor Productivity	-.0177** (.0045)	-.0053 (.0075)	-.0158** (.0052)	.0082 (.0073)
		<u>Aggregate Economy</u>		
		Short Run	Long Run	
TFP		-.0044 (.0043)	.0041 (.0048)	
Labor Productivity		-.0111** (.0038)	-.0024 (.0048)	

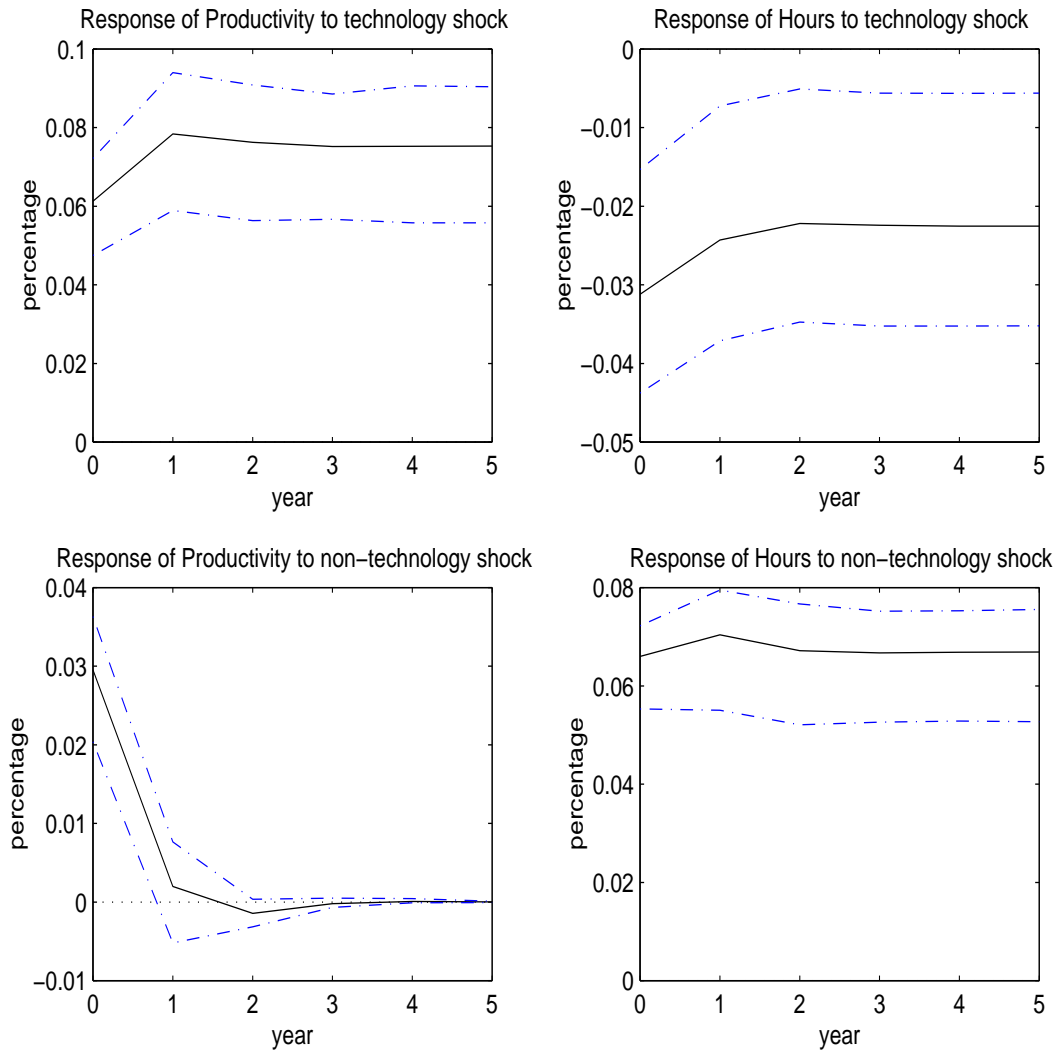
Note: The numbers denote the short- and long-run response of hours to a permanent increase in productivity. Those in parenthesis are standard errors. The aggregate economy reflects the nonfarm business sector.

Figure 1: Impulse Responses of TFP and Hours – Aggregate Manufacturing



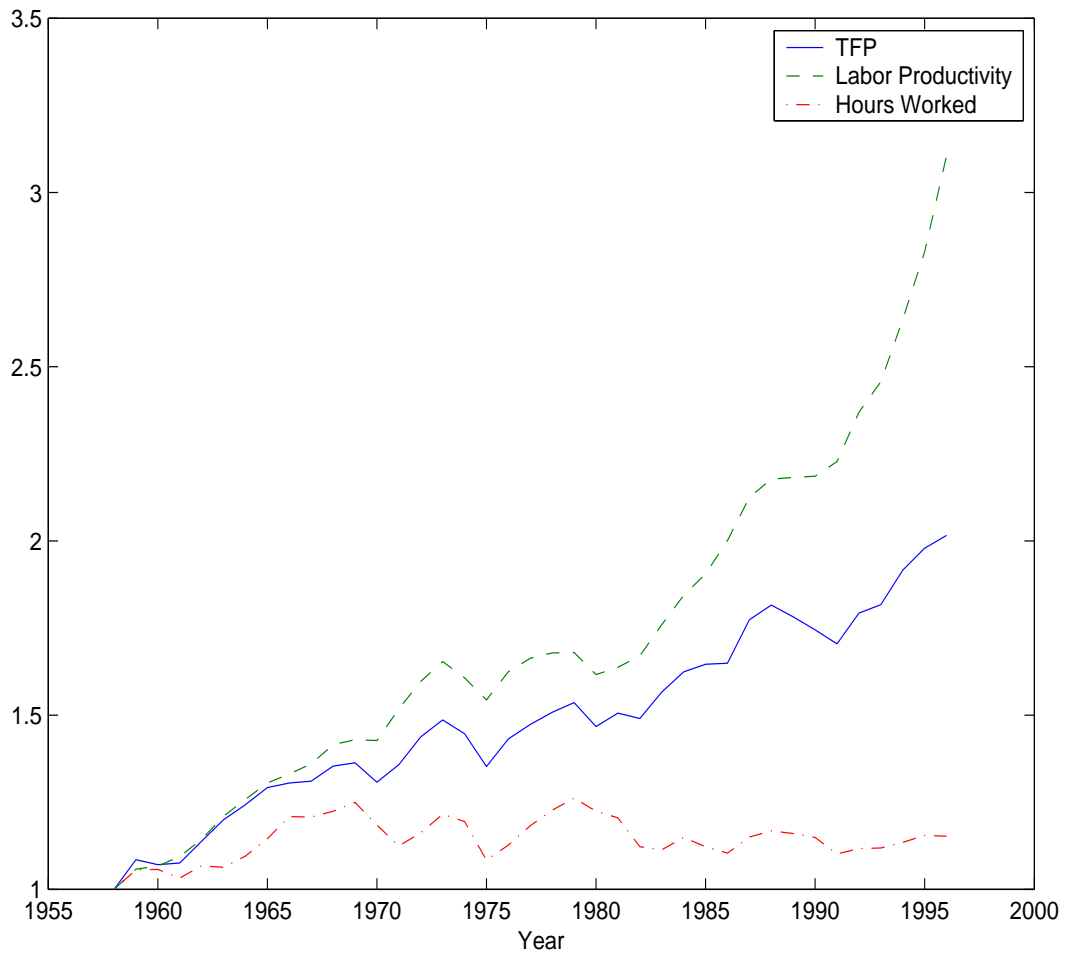
Note: Figure depicts the impulse response of TFP and hours to (one-standard-deviation) technology and non-technology shocks. The dotted lines represent the 90 percent confidence intervals based on bootstrapping 500 draws.

Figure 2: Impulse Responses of TFP and Hours – Agricultural Chemicals



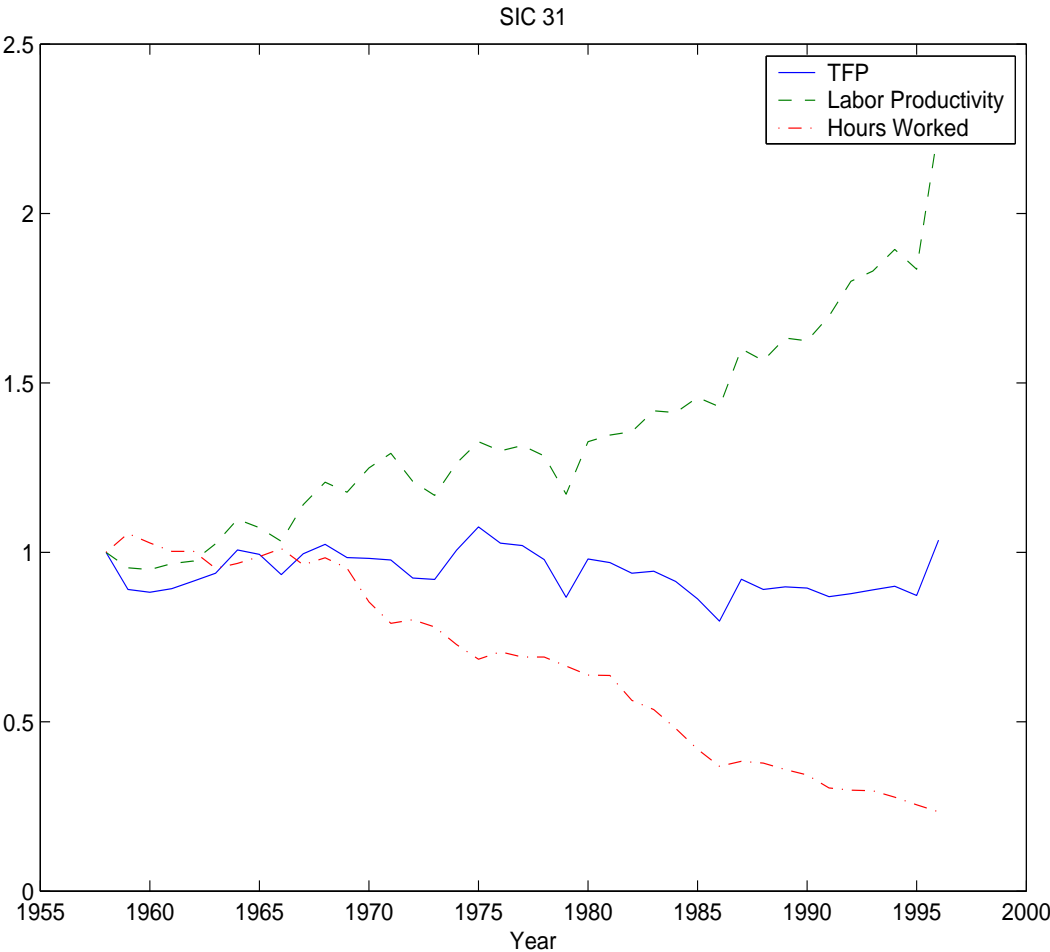
Note: Figure depicts the impulse response of TFP and hours to (one-standard-deviation) technology and non-technology shocks. The dotted lines represent the 90 percent confidence intervals based on bootstrapping 500 draws.

Figure 3: TFP, Labor Productivity, and Hours – Manufacturing



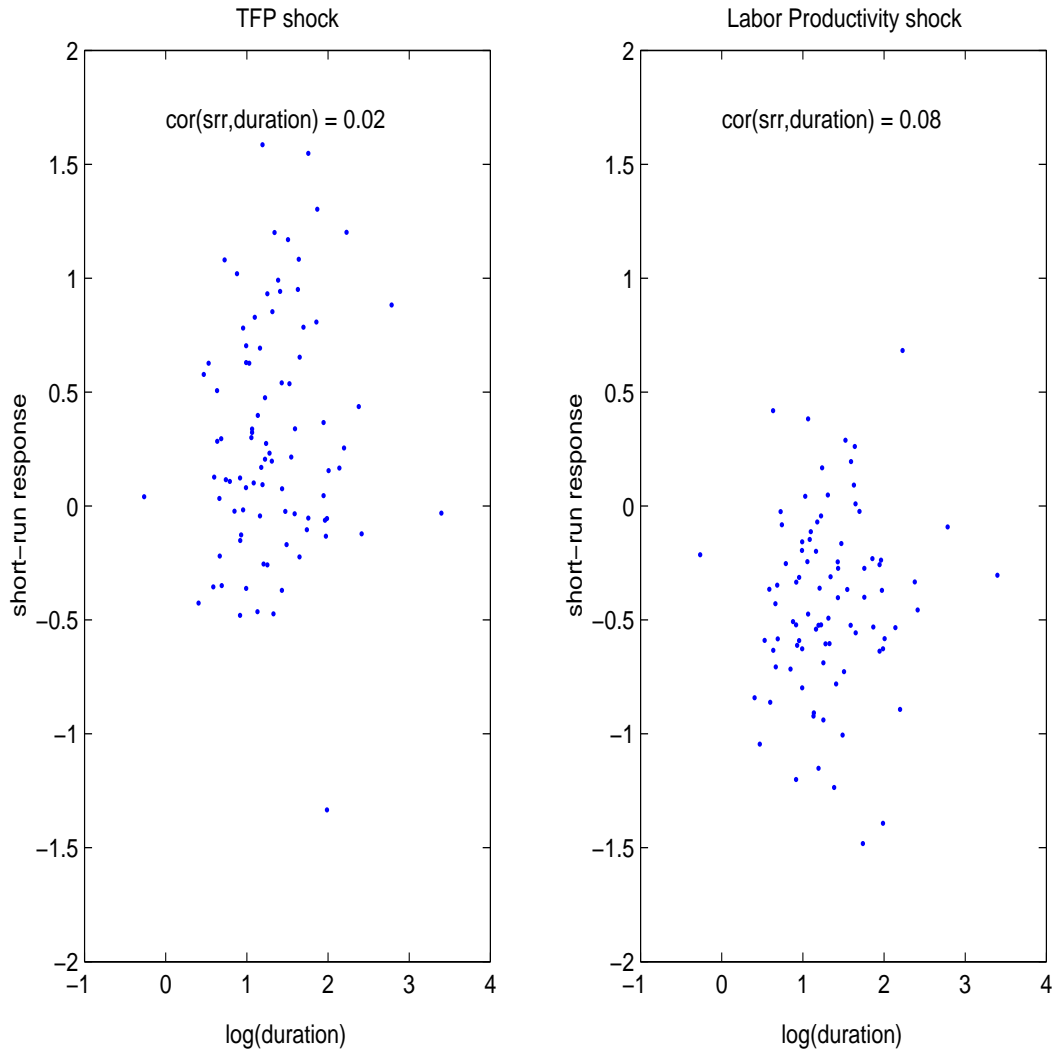
Note: All variables are relative to the 1958 value. Labor productivity is value added output divided by total hours worked.

Figure 4: TFP, Labor Productivity, and Hours – Leather and Leather Products



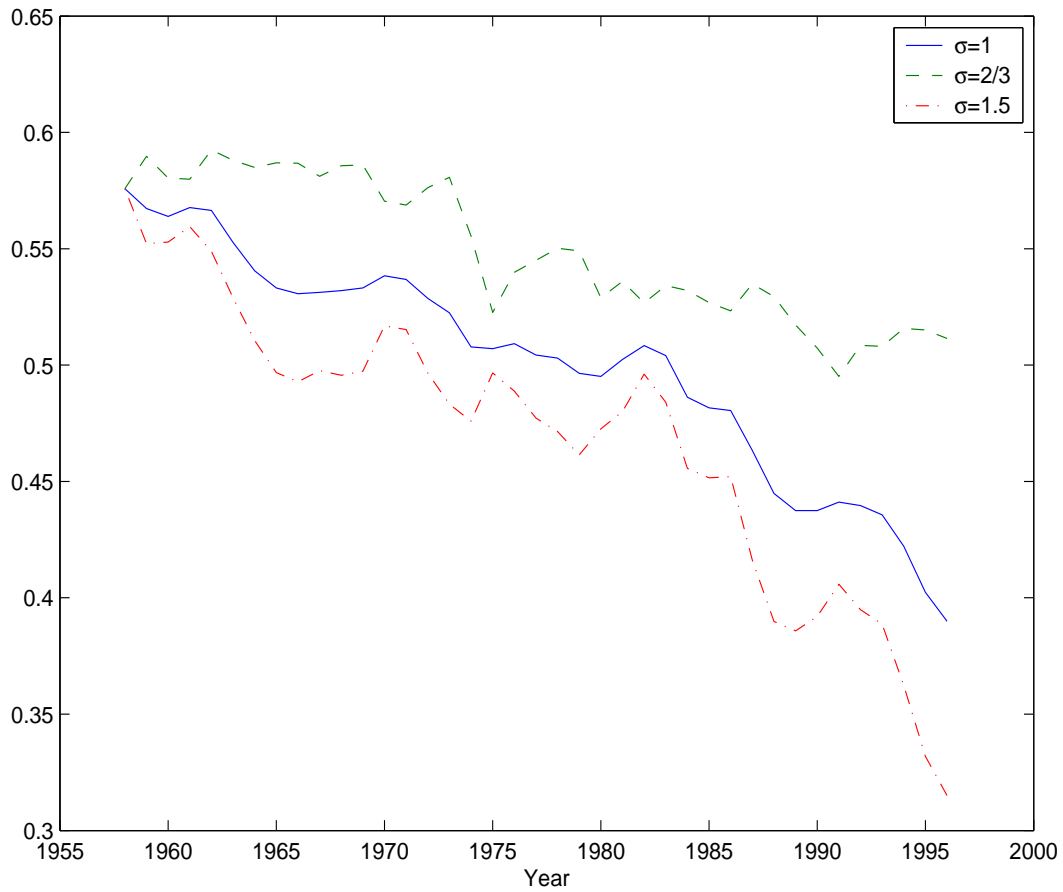
Note: All variables are relative to the 1958 value. Labor productivity is value added output divided by total hours worked.

Figure 5: Price Duration and Hours Response to TFP



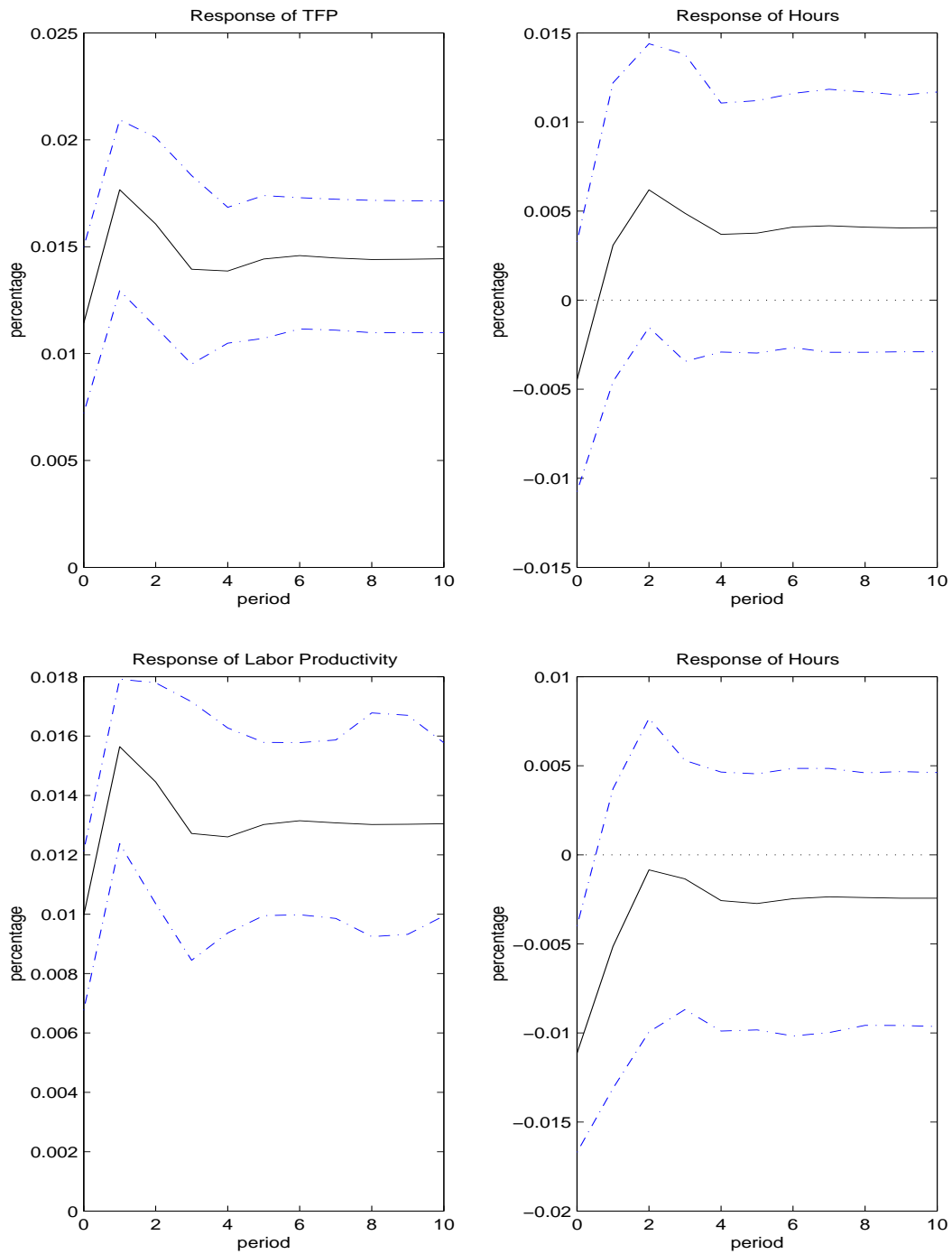
Note: The x-axis denotes the (log of) average monthly duration of industry output price based on Bils and Klenow (2002). The y-axis represents the short run response of hours to a shock that increases industry TFP (or labor productivity in the right panel) by one percent in the long run.

Figure 6: Output-Labor Elasticity: Manufacturing



Note: The figure depicts the output-labor elasticity (α) implied by the equation (4). Three lines correspond to the substitution elasticity between capital and labor (σ) of, respectively, 2/3, 1, and 1.5.

Figure 7: TFP vs. Labor Productivity – Nonfarm Business Sector



Note: The top panels show the responses of aggregate TFP and hours to a (one-standard-deviation) permanent TFP shock; the bottom panels show those of aggregate labor productivity and hours to a (one-standard-deviation) permanent labor productivity shock. The dotted lines represent the 90 percent confidence intervals based on bootstrapping 500 draws.