

Do Technological Improvements in the Manufacturing Sector Raise or Lower Employment?

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Abstract

We find that technology's effect on employment varies greatly across manufacturing industries. Some industries exhibit a temporary reduction in employment in response to a permanent increase in TFP, whereas far more industries exhibit an employment increase in response to a permanent TFP shock. This raises serious questions about existing work that finds that a labor productivity shock has a strong negative effect on employment. There are tantalizing and interesting differences between TFP and labor productivity. We argue that TFP is a more natural measure of technology because labor productivity reflects shifts in the input mix as well as in technology.

Keywords: Technology Shocks, Hours Fluctuations, Sticky Prices

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I. Introduction

Despite controversies concerning the quantitative importance of technology as a source of business cycles, technology's effect on employment is conventionally viewed as expansionary. Recently, a number of studies—Jordi Galí (1999), Michael Kiley (1998), Neville Francis and Valerie Ramey (2002), and Susanto Basu, John Fernald and Miles Kimball (2005)—have reported that favorable technology shocks may reduce total hours worked in the short run. This is an important finding because, if it is confirmed, the fluctuation induced by technological progress may violate a simple fact of the business cycle: output and employment strongly co-move, which has been documented at least since the work of Arthur Burns and Wesley Mitchell (1946).¹

In this article, we ask whether technological improvement of an industry—identified by the permanent components of industry's total factor productivity (TFP)—raises or lowers employment in U.S. manufacturing. According to our VAR analysis of 458 4-digit manufacturing industries for the period 1958–1996, the effect of technology on employment varies vastly across industries. While some industries exhibit a temporary reduction in employment in response to a permanent increase in TFP, there are far more industries in which both employment and hours per worker increase in the short run. Among 458 4-digit industries, 133 industries exhibit a statistically significant increase of hours in response to a favorable technology shock, whereas only 25 industries exhibit a significant decrease in hours in the short run.

Our results contrast with Kiley's; he found a strong negative correlation between the permanent component of labor productivity and employment in most 2-digit manufacturing industries. We do not see these findings necessarily conflicting because we identify technology from permanent components of TFP, while Kiley identifies it from those of labor productivity. We argue that TFP

¹In Galí (1999), Kiley (1998), and Francis & Ramey (2002), 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 increasing returns to scale, utilization, and aggregation effects. In contrast, John 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 reduces inputs in the long run.

is a more natural measure of technology because labor productivity reflects changes in input mix as well as improved efficiency. Disturbances affecting material-labor or capital-labor ratios (e.g., relative input price changes or sectoral reallocation of labor) 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. We show that significant shifts in input mix have occurred in manufacturing and that permanent shocks to input mix are indeed associated with the short-run reduction of hours.

The contractionary effect of technology is often interpreted in favor of the model with sticky prices (e.g., Galí (1999)). We ask whether the variation across industries in the impact of technology on employment can be accounted for by the stickiness of industry-output prices using the recent micro data on average duration of product prices in Mark Bils and Peter Klenow (2004). For 87 manufacturing industries, we do not find a strong correlation between the industry’s employment response and the average duration of industry-output prices.

Our findings are potentially important because *(i)* they undercut a growing strand of literature that uses the short-run impact of technology on employment as evidence against the models with flexible prices, because *(ii)* TFP, rather than labor productivity, is the natural measure of technology, and because *(iii)* TFP and labor productivity behave quite differently at the sectoral level—in particular, shocks that affect labor productivity in the long run do not necessarily involve changes in TFP.

The paper is organized as follows. In Section II, we briefly describe our empirical method, including the VAR and data, and report the estimates on technology’s effect on employment. In Section III, we analyze the difference between the trends in TFP and labor productivity by computing the contribution of input deepening in labor productivity. Section IV provides caveats to our analysis. Section V is the conclusion.

II. Evidence from Industry TFP and Hours

A. Data

We derive our industry data from the NBER-CES Manufacturing Industry Database by Eric Bartelsman, Randy Becker and Wayne Gray (2000), which includes data for 458 4-digit manufacturing industries for 1958–1996 and largely reflects information in the Annual Survey of Manufactures(ASM).² The TFP growth contained in the database is based on measuring separate factor inputs for non-energy materials, energy, labor, and capital. For TFP higher than the 4-digit level, we aggregate 4-digit TFP growth weighted by the industry’s revenue. 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 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 database includes only 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 2-digit manufacturing industry. The ratio of these other labor payments to wages and salaries in 2-digit industries, in turn, is based on information in the National Income and Product Accounts. Industry output reflects the value of shipments divided by the price deflator of industry output. Material expenditure includes expenditure on energy as well as on non-energy materials. Capital’s share is calculated as a residual from labor and material’s share following the database’s convention. This measurement of TFP is correct under the assumptions of perfect competition and constant returns to scale. According to Susanto Basu and John Fernald (1997), Craig Burnside, Martin Eichenbaum and Sérgio Rebelo and (1995), these assumptions are reasonable descriptions of U.S. manufacturing.

²We exclude the “Asbestos Product” industry (SIC 3292) because this time series ended in 1993.

B. Identifying Technology Shocks

Technology shocks are identified by the structural VAR of industry TFP and total hours worked. Fluctuations in industry TFP and hours worked 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).

Let vector Δx_t be $[\Delta z_t, \Delta l_t]'$, where Δz_t and Δl_t denote TFP growth and labor-hours growth, respectively. Let ϵ_t be the vector of two shocks $[\epsilon_t^z, \epsilon_t^l]'$, where ϵ_t^z and ϵ_t^l denote the technology and non-technology shocks, respectively. In our data, both TFP and hours are integrated of order one. Thus, Δx_t can be expressed as a (possibly infinite) distributed lag of both types of shocks:³

$$\Delta x_t = C(L)\epsilon_t = \sum_{j=0}^{\infty} C_j \epsilon_{t-j} \quad (1)$$

$$\text{with } E[\epsilon_t \epsilon_t'] = I, \text{ and } E[\epsilon_t \epsilon_s'] = 0, t \neq s.$$

Our identifying restriction corresponds to $C^{12}(1) = \sum_{j=0}^{\infty} C_j^{12} = 0$. The MA representation is

$$\Delta x_t = A(L)e_t = \sum_{j=0}^{\infty} A_j e_{t-j} \quad (2)$$

$$\text{with } A_0 = I, E[e_t e_t'] = \Omega, E[e_t e_s'] = 0, t \neq s,$$

where $\Omega = C_0 C_0'$, $e_t = C_0 \epsilon_t$, and $C_j = A_j C_0$. The MA representation $A(L)$ is obtained from the VAR of

$$\Delta x_t = B(L)\Delta x_{t-1} + e_t = \sum_{j=1}^p B_j \Delta x_{t-j} + e_t. \quad (3)$$

We estimate the VAR (3) using data aggregated to 2-, and 3-digit levels, aggregating from 4-digit data as described above. We also estimate pooled specifications on disaggregated data, restricting some coefficients to be identical across sub-industries. The pooled data provide more observations:

$$\Delta x_t^i = B(L)\Delta x_{t-1}^i + e_t^i, \text{ for } i = 1, \dots, N,$$

³The constant terms are suppressed here for expositional convenience.

where N is the number of sub-industries. We assume that $B(L)$ and Ω are the same across the sub-industries but allow for different average growth rates in TFP and hours (constant terms in the VAR) across sub-industries.⁴ Most of our discussions are based on aggregated data unless otherwise specified. All VARs have a lag of one year.⁵ The standard errors are computed by bootstrapping 500 draws.

Lawrence Christiano, Martin Eichenbaum and Robert Vigfusson (2004) show that whether hours are treated as stationary in levels or in first differences is important for the response of hours to technology in a structural VAR. The issue of stationarity of hours worked remains controversial (e.g., Matthew Shapiro and Mark Watson (1988)), and the stationarity is often motivated by the so-called balanced growth path at the aggregate level. At the industry level, however, a permanent change in productivity may well imply a long-run change in hours worked through sectoral reallocation of labor, and hours are, in fact, non-stationary in most industries. For example, at a 10 percent significance level, we can reject the null hypothesis of unit root for only one out of 20 industries. Thus, hours enter as first differences in our analysis of sectoral VARs.

C. *Results from an Industry VAR*

Figure 1 displays the impulse 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 1 percent), hours worked increase 0.35 percent at impact. Hours worked continue to rise for two years, until it reaches the new steady state, 1.3 percent higher than before. In response to a non-technology shock, TFP increases 0.7 percent initially—which indicates pro-cyclical factor utilization—and returns to the previous level over time. Hours worked increases 3 percent and remains high. The response based on the pooled data shows a similar pattern.

⁴For aggregate manufacturing, durables and non-durables, 2-digit data are used; for a 2-digit (3-digit) industry, 3-digit (4-digit) data are used.

⁵According to the Akaike information criterion (AIC), the optimal lag length is 1 in 304 industries out of 458 industries, and the Schwarz information criterion (SIC) chooses the lag length of 1 for 422 industries. Given the short annual time series, we chose the lag length of 1.

Table 1 lists unconditional and conditional correlations between TFP growth and growth of hours worked.⁶ Overall, growth rates of TFP and hours worked are strongly positively correlated in aggregate manufacturing: unconditional correlation is 0.64 (with standard error of 0.09). The correlation conditional on technology shocks is 0.60 (0.34): the manufacturing industry employs more workers when the efficiency improves permanently. The conditional correlation on non-technology shocks is also positive and significant, 0.76 (0.06): a temporary increase of TFP is associated with longer hours of work.⁷

The correlation conditional on technology ranges from -0.71 in “Lumber and Wood Products except Furniture” to 0.99 in “Apparels and Other Finished Products.” Yet the majority of 2-digit industries show a positive correlation between TFP and hours conditional on technology shocks; 10 industries exhibit 0.5 or higher. Among those statistically significant, eight industries exhibit a positive correlation, whereas only one industry exhibits a statistically significant negative conditional correlation. This pattern is robust across the level of aggregation.

In terms of the short-run response, Table 2 shows the number of industries with a negative or positive contemporaneous response of hours to technology from the bi-variate industry VARs. The numbers in parentheses represent the cases that are statistically significant at 10 percent. Of the 2-digit industry estimates based on the aggregated data, 14 industries show a positive response (four significant) whereas six industries exhibit a negative response (only one is statistically significant). The result is similar when we use the pooled data. There are 14 (eight significant) positive and six (one significant) negative responses. At the 3-digit level, 93 (37 significant) industries show a positive response, and 47 (12 significant) show a negative response. Again, the estimates based on the pooled data provide a similar pattern. Among the full sample of the 458 4-digit industries,

⁶Following Galí (1999), we compute the conditional correlation on technology based on VAR estimates as follows:

$$cor(\Delta z_t, \Delta l_t | \epsilon^i) = \frac{\sum_{j=0}^{\infty} C_j^{1i} C_j^{2i}}{\sqrt{var(\Delta z_t | \epsilon^i) \cdot var(\Delta l_t | \epsilon^i)}}$$

for $i = z, l$, where $var(\Delta z_t | \epsilon^i) = \sum_{j=0}^{\infty} (C_j^{1i})^2$ and $var(\Delta l_t | \epsilon^i) = \sum_{j=0}^{\infty} (C_j^{2i})^2$.

⁷Unconditional correlation does not necessarily fall between two conditional correlations because unconditional correlation is not necessarily a weighted average of conditional correlations. A formal proof is available from the authors upon request.

320 (133 significant) industries show a positive response, whereas 138 (25 significant) industries show a negative response. Despite considerable heterogeneity across sectors, technology's effect on employment does not appear strongly inconsistent with the conventional view: technological progress increases the demand for labor. Regarding the quantitative importance of technology shocks, for aggregate manufacturing, technology shocks account for 15 percent of the volatility of the three-year forecast variance of hours worked according to a VAR based on the aggregated data. A relatively small contribution of technology is consistent with previous findings from the structural VAR based on aggregate data where technology is identified by the permanent components of productivity (e.g., Olivier Blanchard and Danny Quah (1989)).

D. *Relation to Sticky Prices*

Our analysis of industry VARs reveals a considerable heterogeneity in the response of hours to technology. A negative response is apparently inconsistent with the prediction of the baseline flexible-price model.⁸ Motivated by employment's negative short-run response to a permanent labor productivity shock in OECD countries, Galí (1999) proposed a sticky-price model as a mechanism capable of generating a negative impact of technology on employment. Intuitively, when price is fixed, the demand for goods remains unchanged, and firms need less input, including labor, to produce the same amount of output, thanks to the improved efficiency.⁹

We ask whether the industry's response of hours (to technology shocks) is systematically correlated with the stickiness of industry-output prices. We take advantage of the recent study by Bils & Klenow (2004), who compute the average price-change frequency of 350 goods and services from the price quotes collected by the BLS for 1995-1997. For 87 manufacturing industries, we are able

⁸With adjustment costs to investment, an RBC model with flexible prices can exhibit a negative response of hours to technology (e.g., Urban Jermann (1998)).

⁹Michael Dotsey (2002) and Jordi Galí, David López-Salido and Javier Vallés (2003) show that technology's effect on employment also depends on monetary policy: employment can increase even under the sticky price model if the monetary authority strongly accommodates technology shocks.

to match the SIC code with the entry-level items (ELIs).¹⁰ In matching the two data sets, each ELI corresponds to a 4-digit SIC industry for 44 goods. For 11 goods, one ELI item corresponds to multiple 4-digit SIC industries. In this case, we aggregate the industries' TFP and hours. For 32 goods, multiple ELIs belong to one 3- or 4-digit SIC industry. In this case, the CPI weights from the BLS are used to calculate the average price-change frequency of the goods. For 87 goods, the average duration during which prices remain fixed (the inverse of average price-change frequency) is 3.4 months.

The left panel of Figure 2 shows the relationship between the short-run response of hours to technology (y -axis) and average duration of industry-product prices (x -axis) for 87 manufacturing industries. Since industries may have experienced different degrees of technological change over time, we normalize the technology shocks across industries. We consider a technology shock that increases TFP 1 percent in the long run (instead of the conventional one-standard-deviation shock). Under the sticky-price hypothesis we expect a negative correlation between the short-run response of hours worked and average price duration. No systematic relationship appears; the cross-sectional correlation between the short-run response of hours worked and average duration of prices is -0.01. The right panel of Figure 2 shows the cross-sectional relationship between price stickiness and the short-run response of hours to a permanent labor productivity shock (that increases the labor productivity 1 percent in the long run in a bivariate VAR of labor-productivity growth and hours growth, as in Galí (1999)) and average price duration. Again, we do not find a strong correlation between the response of hours worked and average duration of prices.

Our evidence—a near-zero cross-sectional correlation between the employment response to technology and average price duration—should not necessarily be viewed as evidence against the importance of sticky prices in general.¹¹ Rather, a low correlation suggests that price stickiness may not be a primary reason why firms employ hours differently in the face of technological progress.

¹⁰To calculate the Consumer Price Index, 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).

¹¹Our analysis has a limited implication because the Bils-Klenow measure covers retail prices, whereas manufacturing output is more closely related to producers' prices.

Price stickiness should generate contractionary effects of technology shocks only if there are no inventories. If firms carry a non-negligible amount of inventories, production does not have to equal sales. In response to a favorable cost shock, firms can expand output relative to sales and build up inventories for future sales. Mark Bilal (1998) finds that average inventory-sales ratios have a positive and significant effect in accounting for the contemporaneous correlation between growth rates of employment and labor productivity in manufacturing. Yongsung Chang, Andreas Hornstein and Pierre-Daniel Sarte (2004) find that, for 98 manufacturing industries, an industry’s employment response to technology is strongly correlated with the storability (measured by the average service life) of industry products: an average inventory-sales ratio that is 1 percent larger (owing to the longer average service-life of an industry’s product) results in a 0.55-percentage-point larger short-run response of employment (with a standard deviation of 0.19), while the coefficient on the average price duration of an industry’s output has a negative sign but is statistically insignificant.¹²

III. TFP vs. Labor Productivity

Our results appear at odds with Kiley’s, which show that the permanent components of labor productivity and employment are negatively correlated in 15 (out of 17) 2-digit manufacturing industries for 1968:II–1995:IV. When we use labor-productivity growth (instead of TFP) in our bivariate VAR, we also find a strong negative response of hours worked in most industries. In Table 3, at the 2-digit level, 18 (nine significant) industries show a negative response to a permanent increase in labor productivity, whereas only two (zero significant) industries show a positive short-run response. A similar pattern is found across the level of aggregation and the estimation method.

We argue that TFP is a more natural measure of technology because labor productivity reflects input mix as well as efficiency. Under constant returns to scale, labor-productivity growth $\Delta(y-l)_t$

¹²By contrast, Mikael Carlsson (2003) and Domenico Marchetti and Francesco Nucci (2005) provide evidence supporting the sticky-price hypothesis based on, respectively, Swedish and Italian manufacturing data. Both studies use the method of Basu, Fernald & Kimball (2005) to correct for the cyclical component in the TFP and find that the negative correlation between hours and the corrected measure of TFP is more pronounced in sectors with stickier prices.

can be expressed as TFP growth and input deepening (increase of material-labor and capital-labor ratios):

$$\Delta(y - l)_t \simeq \Delta z_t + \alpha_{m,t} \Delta(m - l)_t + \alpha_{k,t} \Delta(k - l)_t \quad (4)$$

where m and k denote the (logs of) material and capital input, respectively, and $\alpha_{m,t}$ and $\alpha_{k,t}$ denote output elasticities (measured by revenue shares) of material and capital, respectively. Non-technology factors, such as changes in relative input prices, affect labor productivity, whereas such changes alone will not affect TFP. Table 4 summarizes the decomposition of the average labor productivity growth based on (4) for 1958-1996. For aggregate manufacturing, the average annual growth rate of labor productivity was 2.71 percent. This growth consists of a 0.9 percent increase due to TFP, a 1.22 percent increase due to an increased material-labor ratio ($\alpha_m \Delta(m - l)$), and a 0.46 percent increase due to an increased capital-labor ratio ($\alpha_k \Delta(k - l)$). Changes in input mix account for a large share of labor productivity growth across 2-digit industries.

The difference between TFP and labor productivity is dramatic in some industries. Figure 3 shows that, in “Leather and Leather Products,” TFP exhibits no apparent trend, whereas labor productivity exhibits a strong trend because of the continuous decline in hours worked over time. For aggregate manufacturing, we cannot reject the null-hypothesis of no co-integration between TFP and labor productivity at a 10 percent significance level. At the 2-digit level, the null hypothesis of no co-integration cannot be rejected for 17 industries at a 10 percent significance level.

If permanent shocks to labor productivity reduce hours, but permanent shocks to TFP do not, then some permanent shocks to inputs must reduce hours in the short run. Consider a bivariate VAR of the growth rate of non-labor input per hour ($\Delta(n - l)_t$) and the growth rate of hours worked (Δl_t): $[\Delta(n - l)_t, \Delta l_t]' = C(L)\varepsilon_t$. The non-labor input growth is the weighted (by their cost shares) sum of material and capital growth. The long-run restriction, $C^{12}(1) = 0$, distinguishes between the shocks that increase non-labor input per hour in the long run and those that do not. The first row of Figure 4 shows the responses of $(n - l)_t$ and l_t to permanent shocks to non-labor input per hour. Hours worked indeed decrease in the short run following a shock that increases non-labor input per hour permanently. A similar bivariate VAR is estimated for the material per hour and hours worked (i.e., $[\Delta(m - l)_t, \Delta l_t]' = C(L)\varepsilon_t$) as well as for capital per hour and hours worked (i.e., $[\Delta(k - l)_t, \Delta l_t]' = C(L)\varepsilon_t$). The second row of Figure 4 shows the response of material per

hour and hours worked to a shock that increases the material-labor ratio in the long run. Likewise, the third row shows the response of capital per hour and hours worked to a shock that increases the capital-labor ratio in the long run. While both permanent shocks (to the material-labor and capital-labor ratios) reduce hours in the short run, permanent shocks to the material-labor ratio generate a more pronounced negative response of hours worked.

In sum, we find that TFP and labor productivity behave quite differently at the sectoral level—in particular, there are shocks that affect labor productivity in the long run that do not involve changes in TFP. While the studies based on aggregate data emphasize the technological progress in the form of improved efficiency, the shift in input mix is also important for understanding labor-productivity growth at the sectoral level. For example, increased outsourcing of intermediate products and business services may account for the substitution of material input for labor in manufacturing. (See Almas Heshmati (2003) for a survey on outsourcing’s effect on the measurement of productivity.)

IV. Some Caveats

We provide some caveats regarding the identification of technology from measured TFP. We are concerned with mismeasurement due to increasing returns to scale, factor utilization, and imperfect competition, as well as potential specification errors in the VAR due to omitted variables.

A. Comparison with Basu et al.

Basu et al. (2005) propose a method to correct measured TFP for increasing returns and factor utilization. The key equation to estimate is the sectoral production function:

$$\Delta y_t = \gamma \Delta x_t + \beta \Delta h_t + \Delta z_t \tag{5}$$

where $\Delta x_t = \alpha_m \Delta m_t + \alpha_k \Delta k_t + \alpha_l \Delta(e_t + h_t)$, and Δy_t , Δz_t , Δe_t and Δh_t are growth rates of, respectively, output, technology, employment, and hours per worker. The basic insight of Basu et al. is that increases in observed inputs (hours per worker) can be a proxy for unobserved changes in utilization (capacity utilization and labor effort). Following Basu et al., we estimate the

system of Equation (5) (separately for durable and non-durable industries) based on 2-digit data using the 3SLS. The coefficient for utilization is restricted to be common across sub-industries. We use the instruments suggested by Basu et al. (2005): the growth rates of oil prices and real military government spending (current and one-period lagged values) and monetary policy shocks (one-period lagged values).¹³ According to Table 5 the median estimate for the returns to scale, γ , is 1.15. The factor utilization parameter, β , is 0.17 and 0.76 for durables and non-durables, respectively. The estimates are not identical to those in Basu et al. because of the differences in the data set (KLEM in Basu et al. vs. NBER database in ours).¹⁴ The residuals from the estimated production functions are aggregated to obtain the aggregate technology of manufacturing. We call this measure of technology Basu-TFP. We obtain four types of Basu-TFP based on 2- and 4-digit production functions as well as on gross and value-added output.¹⁵

Given these productivity measures, we estimate a structural VAR of productivity and hours with the same long-run restriction: only technology has a long-run effect on productivity. Figure 5 shows the response of hours from the bivariate VARs with eight different productivity measures: uncorrected TFP (1st row), 2-digit Basu-TFP (2nd row), 4-digit Basu-TFP (3rd row), and labor productivity (4th row), each measure based on gross output (1st column) and value-added output (2nd column). When the TFP is corrected for the returns to scale and factor utilization based on 2-digit production functions, hours worked decreases in a significant and persistent way as in Basu et al. When 4-digit production functions are used, the hours worked still decrease in the short run but not in a significant way.

Table 6 shows the number of industries with a positive or negative short-run response of hours from bivariate VARs of Basu-TFP and hours worked. When TFP is corrected for returns to scale and factor utilization, there are more industries with a negative response of hours in the short run. While Basu et al.'s work is an important contribution that constructs the technology measure from a micro production structure, we interpret the negative impact of technology with caution.

¹³We thank John Fernald for providing the instruments used in Basu et al.

¹⁴For example, Basu et al.'s estimates for β are 1.34 and 2.13 for durables and non-durables, respectively.

¹⁵The value-added-based TFP growth is obtained by $\Delta\tilde{z} = \frac{\Delta z}{1-\alpha_m}$, where Δz is the gross-output-based TFP, the estimated residual from the gross production function (5).

First, we found that the estimates of production functions are somewhat sensitive to the choice of instruments (for example, to whether the current values of instruments are included or not.). Second, most explanatory power of the instruments stems from the oil-price changes which tends to be more transitory than a typical business cycle. As Bils (1998) points out, we would expect a greater use of increased factor utilization for more transitory shocks (which may result in a greater degree of correction in TFP). Finally, we note that despite a negative impact in the aggregate, the short-run response of hours from the industry VAR using the Basu-TFP still shows no cross-sectional correlation (-0.02) with the Bils-Klenow measure of prices stickiness.

B. Markup

When the TFP measure in the database is constructed, the capital share is computed by the residual share ($\alpha_k = 1 - \alpha_m - \alpha_l$). This implicitly assumes that the price-cost markup is 1. If the true markup is greater than 1, input and TFP may be spuriously correlated. When the true markup is μ , measured TFP growth (incorrectly assuming a markup of 1) is:

$$\Delta z_t = \Delta z_t^* + (\mu - 1)[\alpha_m(\Delta m_t - \Delta k_t) + \alpha_l(\Delta l_t - \Delta k_t)] \quad (6)$$

where Δz_t^* denotes the true TFP growth and α 's denote revenue shares. Table 7 reports the short- and long-run responses of hours to technology from the bivariate VAR of Δz_t^* and Δl_t assuming, respectively, $\mu = 1.05$ and $\mu = 1.1$ in (6).¹⁶ As the markup ratio increases, the response of hours worked tend to decrease in the short run as well as in the long run. In fact, the estimated short-run response of hours decreases to -0.27 (with standard error of 0.78) when the markup is 1.1 and the value-added TFP is used. Nevertheless, given the small profit rates reported in manufacturing over the years (e.g., Basu & Fernald (1997)), the average markup of 1.1 appears high.

C. VAR Specification

John Shea's study (as well as ours) estimates the dynamic response of hours to technology from the structural VAR. Shea makes use of direct measures such as R&D and patent applications.

¹⁶We thank Jordi Galí for suggesting this exercise.

Confronted with an identification problem, he imposes a restriction on the contemporaneous effects (whereas we use the long-run restriction).¹⁷ While the identification based on the long-run restriction is widely used and consistent with a large class of macro models, it has shortcomings, too. First, it requires no trend in the intensity of factor utilization.¹⁸ The workweek of production workers has declined persistently over decades. If this trend affected the intensity of labor effort, the long-run movement of TFP may also reflect such changes. Second, recent studies report that an estimated dynamics identified by the long-run restrictions is sensitive to the medium-run movement (Jon Faust and Eric Leeper (1997)) and omitted variables in the VAR (Christopher Erceg and Luca Guerrieri and Christopher Gust (2003)).

To address potential specification errors due to a small scale VAR, we compare the short-run responses of hours from our bivariate VAR to those from the alternative (larger scale) VARs. The first alternative specification we consider includes aggregate TFP. For each 4-digit industry, we estimate a tri-variate VAR of $[\Delta \text{Agg. } TFP_t, \Delta TFP_t, \Delta l_t]' = C(L)\epsilon_t$ where the innovation vector ϵ_t consists of aggregate technology shock, sectoral technology shock, and non-technology shock. We distinguish three fundamental shocks based on a long-run restriction. Neither the sectoral technology shock nor the non-technology shock affects aggregate TFP in the long run: $C^{12}(1) = C^{13}(1) = 0$. The non-technology shock does not affect the sectoral TFP in the long run: $C^{23}(1) = 0$. We then compute the short-run response of hours to sectoral technology by the contemporaneous effect of the sectoral technology shock on hours worked: C_0^{32} . The sectoral technology we identify reflects the sectoral technology that has no impact on aggregate TFP in the long run. This restriction may be justifiable at the 4-digit industry level where the sector is too small for a sectoral TFP to affect the level of aggregate TFP in the long run in a significant way. The second alternative specification includes other input variables ($[\Delta TFP_t, \Delta l_t, \Delta k_t, \Delta m_t]' = C(L)\epsilon_t$). The same long-run restriction is used to identify the technology shock of the sector: $C^{12}(1) = C^{13}(1) = C^{14}(1) = 0$.

¹⁷In Shea, the technology variable is placed last in the VAR. Empirically, innovations to industry output are positively correlated with innovations to R&D and patent applications. Placing technology last highlights an accelerator mechanism running from industry activity to technology—i.e., R&D is encouraged by the output demand, but an instantaneous impact of technology shocks on output is not allowed.

¹⁸This assumption is also required for the Basu et al. method to identify technology from the measured TFP.

The first graph in Figure 6 plots the short-run responses of hours worked from tri-variate VARs against those from our benchmark bi-variate VARs. Inclusion of aggregate TFP has a non-negligible impact on the estimate of the short-run response of hours to technology. The magnitude of the responses of hours worked increases (in absolute value) overall. This makes sense because the sectoral technology shock has a small (or zero) income effect in labor supply. Yet the ordering and the signs are similar to those from the bivariate sectoral VAR and the cross-sectional correlation between two estimates across 458 4-digit industries is 0.82. The second graph of Figure 6 shows that inclusion of other input variables does not have a very significant effect on the estimates of the short-run response of hours: the cross-sectional correlation between two estimates is 0.85. In sum, our conclusion based on the short-run employment effect of technology from the bi-variate VARs does not seem significantly sensitive to the omission of aggregate TFP or other input variables.

D. *Aggregate Economy*

We showed that there is a tantalizing difference in the response of hours to stochastic trends in TFP and labor productivity in manufacturing. While our analysis focuses on manufacturing industries because the reliable data on capital are available at the detailed disaggregate level, many previous empirical works concern the aggregate economy.¹⁹ In Figure 7 we compare the short-run responses of hours, respectively, to permanent TFP and labor-productivity shocks for the aggregate non-farm business economy. At the aggregate level, the difference is not as striking as that in the disaggregate data. Nevertheless, there is an important difference. According to the bivariate VARs, following a permanent TFP shock, hours worked slightly decreases (statistically not significant) in the short run, gradually increases, and remains high in the long run—a positive but delayed response; however, hours worked declines significantly following a permanent labor-productivity

¹⁹Gali's (1999) empirical work has recently been disputed on the grounds of mis-specifications along two dimensions. Altig, Christiano, Eichenbaum & Linde (2002) argue that Gali's results are subject to omitted variable bias while Christiano, Eichenbaum & Vigfusson (2004) point out that whether hours are treated as stationary or not matters in a structural VAR. V.V. Chari, Patrick Kehoe and Ellen McGrattan (2004) argue that the long-run identification in a structural VAR may not be consistent with the data-generating process of a standard dynamic stochastic general equilibrium model. Yet Francis & Ramey (2002) find evidence in support of Gali.

shock.

V. Conclusion

We find that technological improvement raises employment in many U.S. manufacturing industries. This finding substantially differs from those of previous studies based on labor productivity, which found a negative correlation between the permanent component of labor productivity and employment in manufacturing. We argue that TFP is the natural measure for technology because labor productivity reflects the input mix as well as technology. We show that TFP and labor productivity behave quite differently at the sectoral level and that permanent shocks to input mix are indeed associated with the short-run reduction of hours. Using micro data on average price duration, we ask whether the variation in employment's response to a technology shock across industries is correlated with the average duration of industry-output prices. Among 87 manufacturing industries, we do not find strong evidence of this relationship.

Our findings are potentially important because they undercut a growing strand of literature that uses the short-run impact of technology on employment as evidence against flexible-price business cycle models and because some shocks affecting labor productivity in the long run do not necessarily involve changes in the level of TFP. Given the considerable heterogeneity in the employment effect of technology, more research on micro and historic data—such as Michael Gort and Steven Klepper (1982), Zvi Griliches and Fuden Lichtenberg (1984), Samuel Kortum (1993), Shea (1998), and Basu et al. (2005)—is necessary to better understand what technology shocks are and what they do.

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Table 1: Unconditional and Conditional Correlations in Manufacturing for 1958–1996

SIC	Industry	$cor(\Delta z, \Delta l)$	$cor(\Delta z, \Delta l \epsilon^z)$	$cor(\Delta z, \Delta l \epsilon^l)$
Aggregate Manufacturing		0.638** (0.086)	0.595* (0.340)	0.762** (0.060)
Nondurables		0.478** (0.118)	0.229 (0.564)	0.801** (0.113)
20	Food And Kindred Products	0.203 (0.136)	0.446 (0.503)	0.510 (0.498)
21	Tobacco Products	0.259* (0.152)	0.996 (0.633)	0.759 (0.630)
22	Textile Mill Products	0.256** (0.111)	0.519* (0.288)	-0.689 (0.690)
23	Apparel And Other Finished Products	0.315** (0.149)	0.995** (0.421)	-0.558 (0.561)
26	Paper And Allied Products	0.476** (0.198)	0.487 (0.704)	0.755** (0.115)
27	Printing, Publishing, And Allied Industries	0.323** (0.146)	-0.270 (0.693)	0.736** (0.277)
28	Chemicals And Allied Products	0.207* (0.124)	-0.258 (0.396)	0.582** (0.116)
29	Petroleum Refining And Related Industries	0.085 (0.155)	-0.473 (0.591)	0.793* (0.453)
30	Rubber And Miscellaneous Plastics Products	0.614** (0.088)	0.784** (0.205)	0.721** (0.302)
31	Leather And Leather Products	0.054 (0.164)	-0.355 (0.602)	0.512 (0.406)
Durables		0.658** (0.078)	0.712** (0.205)	0.760** (0.055)
24	Lumber And Wood Products, Except Furniture	-0.101 (0.134)	-0.710** (0.221)	0.508** (0.180)
25	Furniture And Fixtures	0.748** (0.060)	0.848** (0.106)	0.868** (0.110)
32	Stone, Clay, Glass, And Concrete Products	0.675** (0.085)	0.745** (0.224)	0.796** (0.054)
33	Primary Metal Industries	0.444** (0.123)	0.566 (0.528)	0.667** (0.230)
34	Fabricated Metal Products	0.675** (0.069)	0.863** (0.135)	0.690** (0.286)
35	Industrial, Commercial Machinery And Computer Equipment	0.528** (0.113)	0.399 (0.477)	0.733** (0.123)
36	Electronic Equipment, Except Computer Equipment	0.464** (0.134)	0.152 (0.519)	0.863** (0.056)
37	Transportation Equipment	0.506** (0.119)	0.820** (0.401)	0.658** (0.311)
38	Measuring, Analyzing, And Controlling Instruments	0.147 (0.170)	0.119 (0.587)	0.549 (0.465)
39	Miscellaneous Manufacturing Industries	0.405** (0.126)	0.891** (0.421)	0.565 (0.527)

Note: The numbers in parenthesis are standard errors. Those with double asterisks are statistically significant at 5 percent.

Table 2: Short-Run Response of Hours to TFP shock

Data		<u>Number of Industries</u>	
		Positive	Negative
2-digit	aggregated	14 (4)	6 (1)
	pooled	14 (8)	6 (1)
3-digit	aggregated	93 (37)	47 (12)
	pooled	107 (47)	33 (5)
4-digit		320 (133)	138 (25)

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

Table 3: Short-Run Response of Hours to Labor Productivity Shock

Data		<u>Number of Industries</u>	
		Positive	Negative
2-digit	aggregated	2 (0)	18 (9)
	pooled	2 (1)	18 (15)
3-digit	aggregated	25 (6)	115 (60)
	pooled	17 (2)	123 (72)
4-digit		107 (17)	351 (174)

See Note in Table 2.

Table 4: Decomposition of Labor Productivity Growth

	$\Delta(y - l)$	ΔTFP	$\alpha_m \Delta(m - l)$	$\alpha_k \Delta(k - l)$
Manufacturing	2.71	0.90	1.22	0.46
Nondurables	2.34	0.55	1.17	0.57
20 :	2.32	0.45	1.34	0.45
21 :	3.00	-1.05	0.92	2.64
22 :	3.31	1.16	1.94	0.36
23 :	2.51	0.72	1.18	0.67
26 :	2.42	0.49	1.18	0.72
27 :	1.01	-0.07	0.43	0.57
28 :	3.11	0.92	1.19	0.83
29 :	2.88	0.44	2.17	0.26
30 :	2.42	1.38	0.83	0.36
31 :	1.95	0.11	1.12	0.78
Durables	3.00	1.20	1.28	0.38
24 :	1.71	0.46	1.09	0.14
25 :	1.64	0.33	0.82	0.41
32 :	1.88	0.80	0.72	0.30
33 :	1.84	0.54	1.19	0.14
34 :	1.51	0.60	0.62	0.42
35 :	3.71	2.07	1.64	0.60
36 :	5.70	2.92	1.61	0.92
37 :	2.85	0.80	1.92	0.37
38 :	3.46	0.93	1.23	1.21
39 :	2.12	0.66	0.90	0.59

Note: The long-run decomposition is based on Equation (4).

Table 5: Parameter Estimates based on Basu et al. Method

		<u>Returns to Scale(γ)</u>	
Durables			Non-Durables
Lumber, Wood Products (24)	0.92 (0.11)	Food (20)	0.38 (0.41)
Furniture (25)	1.18 (0.08)	Tobacco (21)	1.08 (0.96)
Stone, Clay, Glass (32)	1.36 (0.07)	Textile Mill (22)	0.86 (0.16)
Primary Metal (33)	1.29 (0.09)	Apparel (23)	1.24 (0.16)
Fabricated Metal (34)	1.29 (0.09)	Paper Products (26)	1.48 (0.21)
Non-Electronic (35)	1.67 (0.15)	Printing, Publishing (27)	1.49 (0.26)
Electronic Equipment (36)	1.53 (0.21)	Chemicals (28)	1.52 (0.22)
Transportation Equipment (37)	1.12 (0.07)	Petroleum Refining (29)	0.53 (0.14)
Measuring, Analyzing (38)	0.97 (0.09)	Rubber, Plastics (30)	1.15 (0.08)
Miscellaneous (39)	1.41 (0.18)	Leather (31)	0.39 (0.40)
		<u>Utilization(β)</u>	
Durables		Non-Durables	
0.17 (0.25)		0.76 (0.37)	

Note: The estimates are based on 3SLS (separately for durables and non-durables).

Table 6: Short-Run Response of Hours to Basu-TFP Shock

Data		<u>Number of Industries</u>	
		Positive	Negative
2-digit	aggregated	4 (0)	16 (5)
	pooled	7 (2)	13 (7)
3-digit	aggregated	38 (12)	102 (32)
	pooled	43 (13)	97 (34)
4-digit		161 (43)	297 (100)

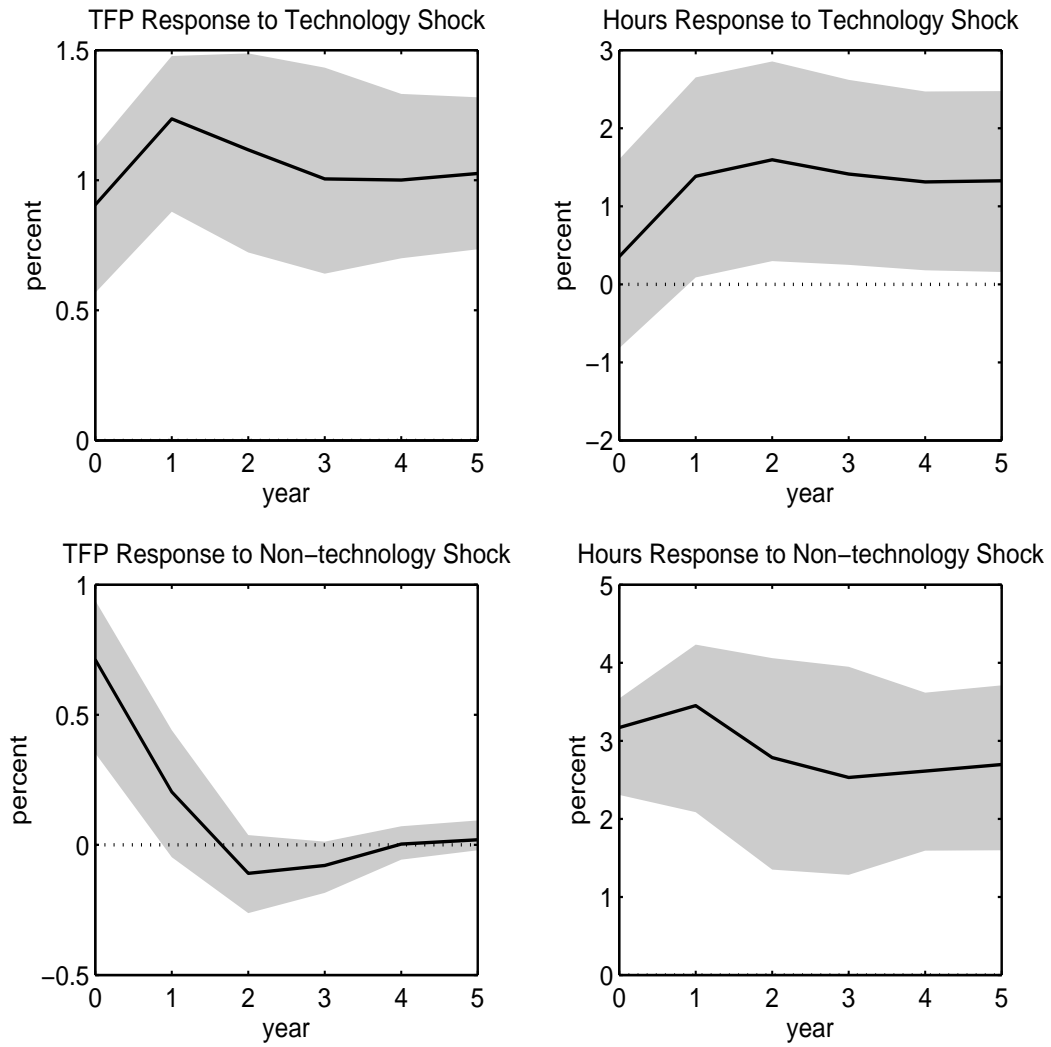
See Note in Table 2.

Table 7: Imperfect Competition

Productivity Measure	Gross Output		Value Added	
	Short Run	Long Run	Short Run	Long Run
TFP ($\mu = 1$)	0.35 (0.73)	1.35* (0.69)	0.49 (0.75)	1.52** (0.73)
TFP ($\mu = 1.05$)	0.25 (0.74)	1.25 (0.77)	0.28 (0.77)	1.27 (0.79)
TFP ($\mu = 1.1$)	0.09 (0.73)	1.09 (0.77)	-0.26 (0.78)	0.38 (0.96)
Labor Productivity	-1.77** (0.47)	0.53 (0.72)	-1.58** (0.54)	0.83 (0.71)

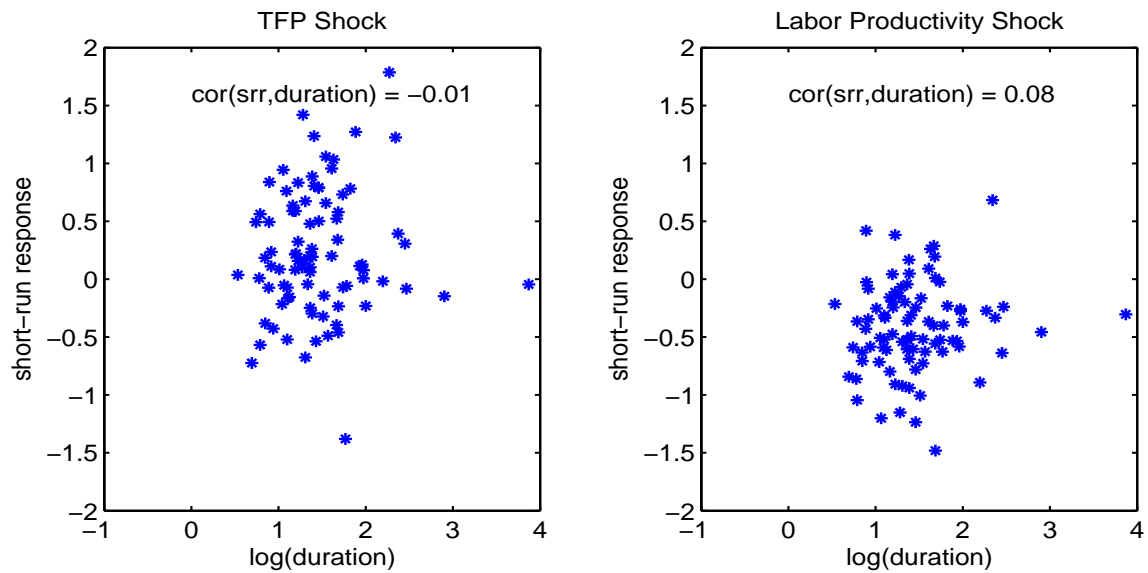
Note: The numbers represent the short-run and long-run responses of hours (in percent) to a permanent TFP or labor productivity shock. Those in parenthesis are standard errors. The aggregate economy reflects the non-farm business sector.

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



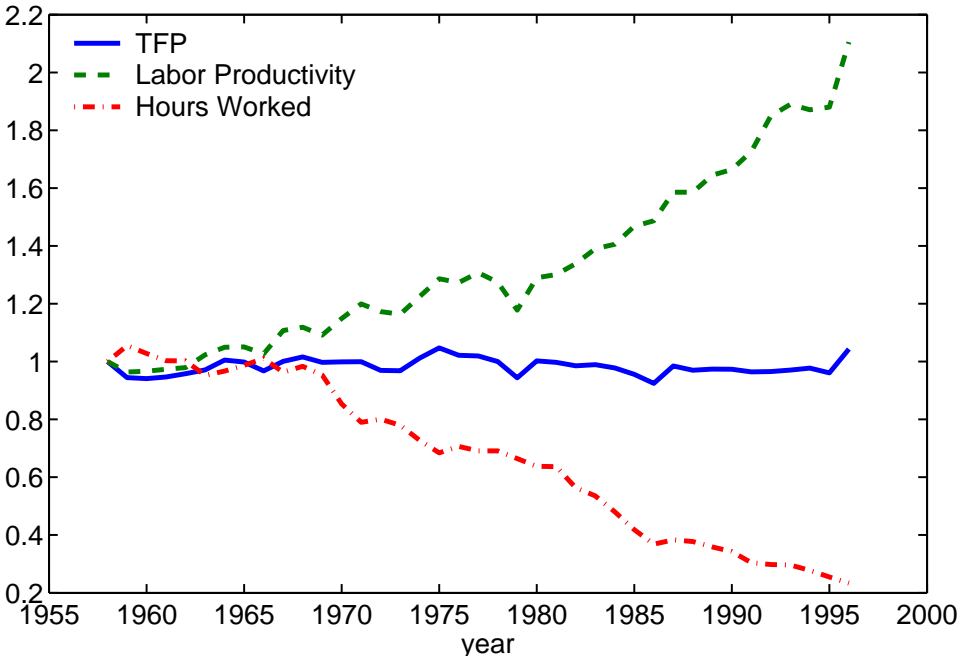
Note: The shaded area represents the 90-percent confidence intervals based on bootstrapping 500 draws.

Figure 2: Price Duration and Hours Response to Technology Shock



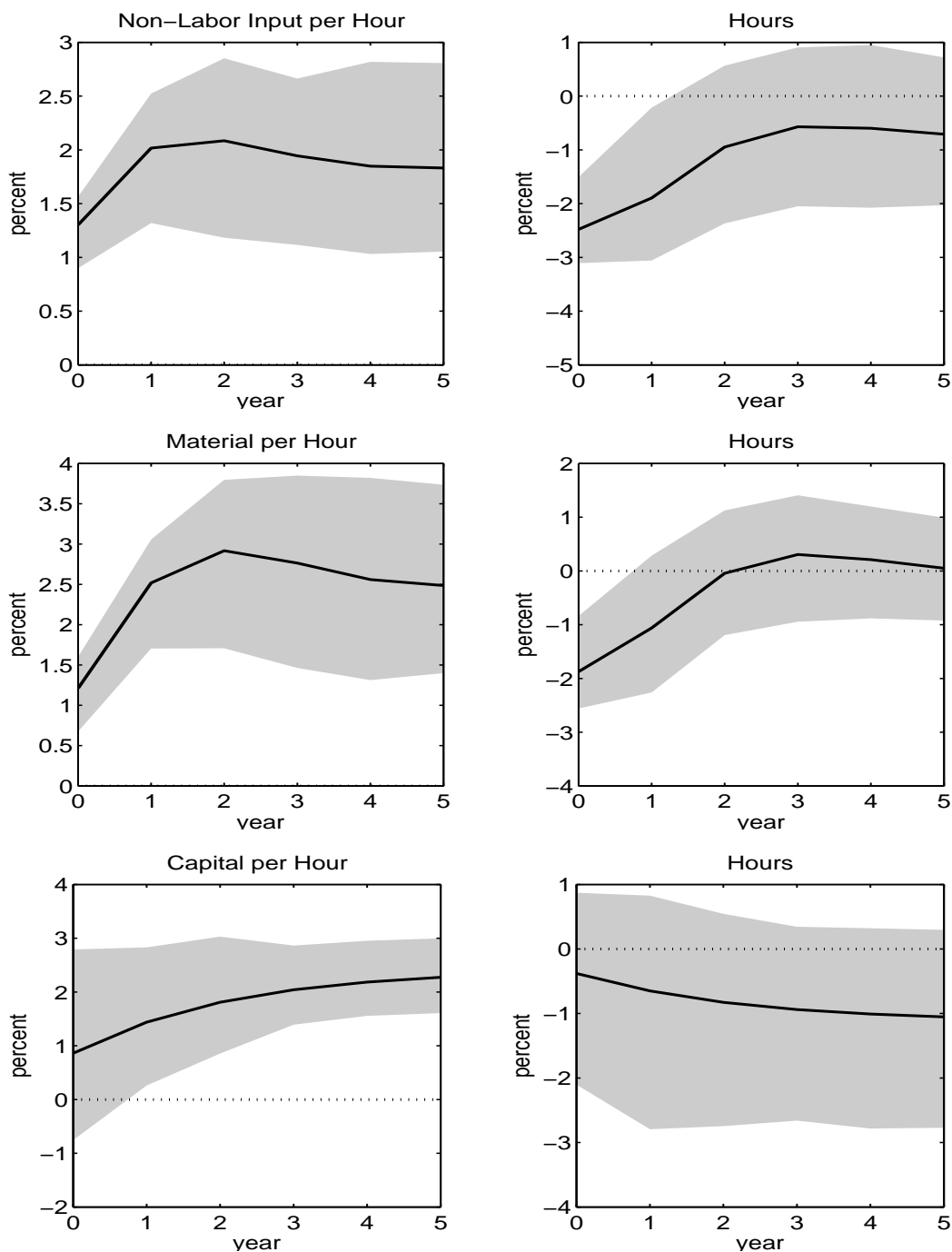
Note: The x -axis is the (log of) average monthly duration of industry output prices. The y -axis is the short-run response of hours to a shock that increases industry TFP (or labor productivity in the right panel) by one percent in the long run.

Figure 3: TFP, Labor Productivity, and Hours – Leather and Leather Products



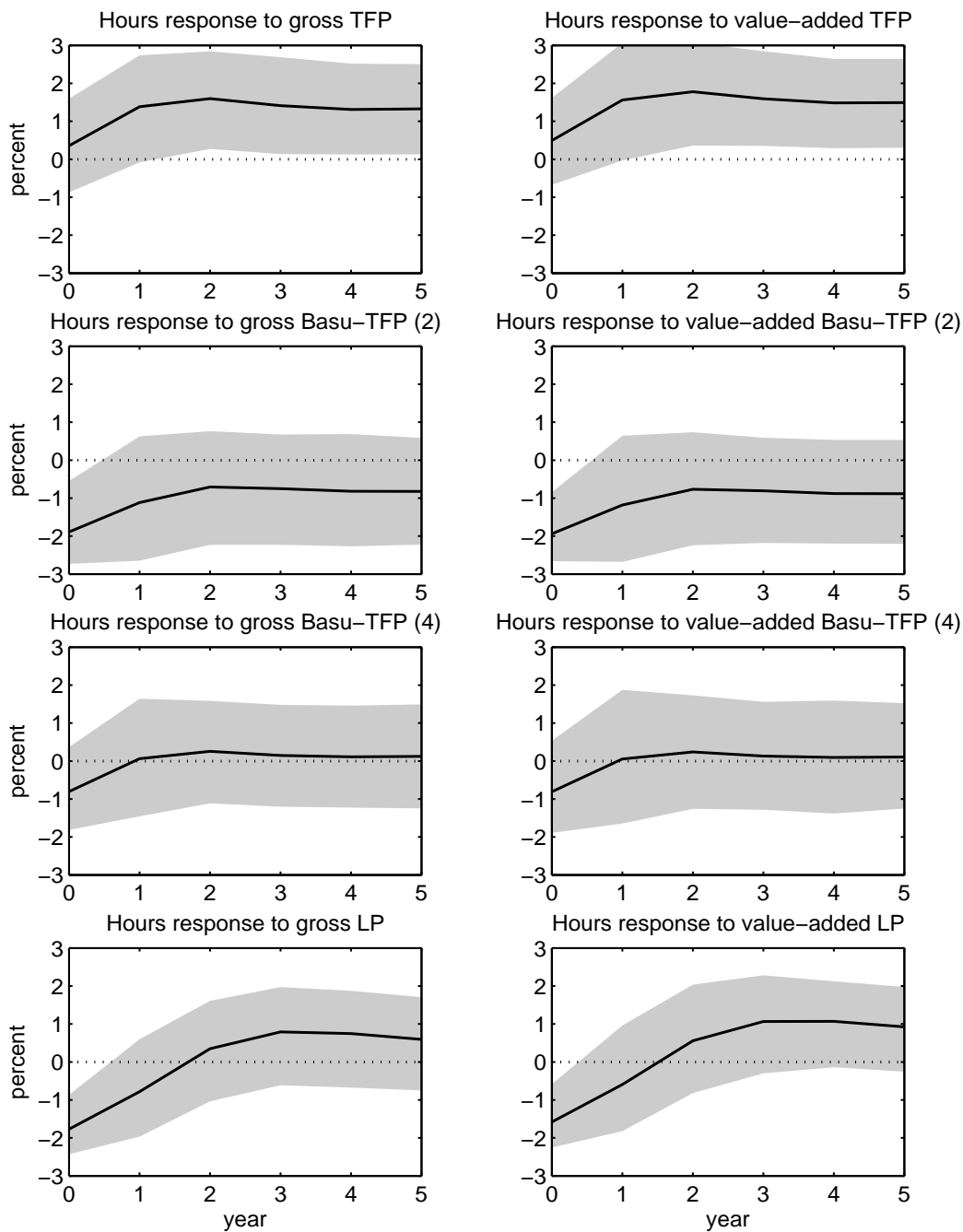
Note: All variables are relative to the 1958 value. Labor productivity is value added divided by total hours worked.

Figure 4: Response of Hours to Input Mix Shocks



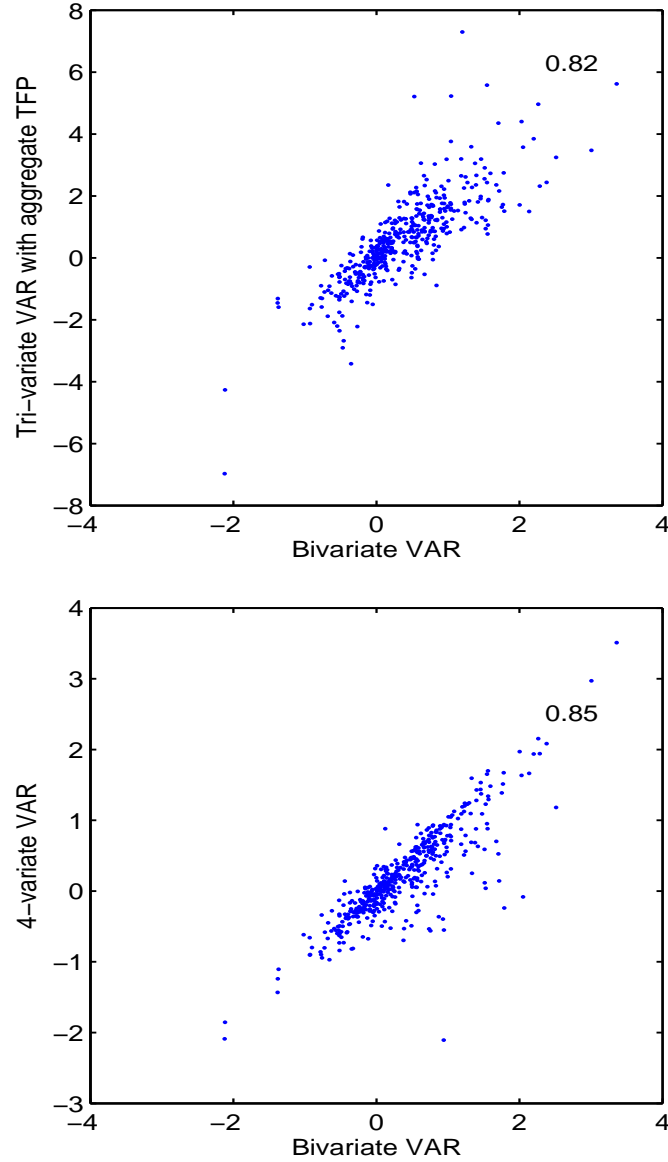
Note: The first row represents the responses of non-labor input per hour ($n-l$) and hours (l), respectively, to a one-standard-deviation permanent shock to non-labor input per hour. The second row represents the responses of material per hour ($m-l$) and hours, respectively, to a one-standard-deviation permanent shock to material per hour. The third row represents the responses of capital per hour ($k-l$) and hours, respectively, to a one-standard-deviation permanent shock to capital per hour.

Figure 5: Hours Response to Various Measures of Productivity



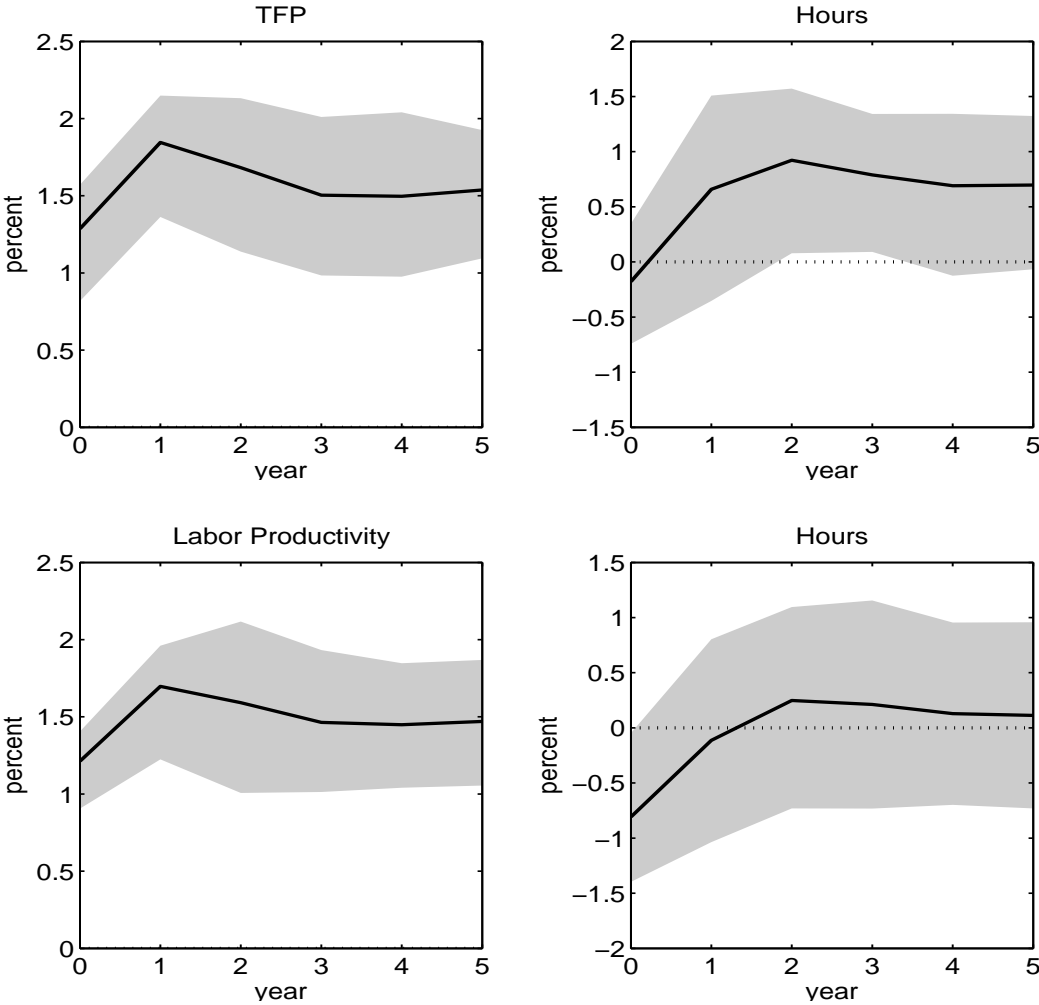
Note: The figures in the left column use productivity measures based on gross output. Those in the right column use productivity measures based on value-added output. The first row shows the hours responses when TFP is used. The second row shows the responses when the Basu-corrected TFP is aggregated from the 2-digit industry production functions. The third row shows the responses when the Basu-corrected TFP is aggregated from the 4-digit industry production functions. The last row shows the responses when labor productivity is used.

Figure 6: Robustness to a VAR Specification



Note: x -axis: short-run responses of hours to permanent TFP shocks from the 4-digit bivariate VARs. y -axis: short-run responses of hours to industry TFP shocks from tri-variate VARs where the third variable is aggregate TFP growth (top graph) and those from the 4-variate VARs where the 3rd and 4th variables are material and capital input growth (bottom graph).

Figure 7: Aggregate Economy: TFP vs. Labor Productivity Shocks



Note: The first (second) row represents the responses of the aggregate non-farm business economy to a one-standard-deviation permanent TFP (labor productivity) shock.