A Quarterly, Utilization-Adjusted Series on Total Factor Productivity[1]

John Fernald
Federal Reserve Bank of San Francisco
August 16, 2009

Preliminary and incomplete [2,]

This note describes a real-time, quarterly series on total factor productivity (TFP) for the

U.S. business sector, adjusted for variations in factor utilization—labor effort and capital's

workweek. The utilization adjustment follows Basu, Fernald, and Kimball (BFK, 2006). Using

relative prices and input-output information, the series is also decomposed into separate TFP and

utilization-adjusted TFP series for equipment investment (including consumer durables) and

"consumption" (defined as business output less equipment and consumer durables).

Academic researchers and policymakers frequently want quarterly measures of

technology, e.g., to feed into models. Relatively crude measures of the Solow residual are easy

to construct. But more careful quarterly measures that better correspond to theoretical concepts

are more difficult to construct or find. With annual data, in contrast, there are several high-

---

[1] I thank several research assistants who have worked with me on this project, most notably Kyle Matoba (who cleaned up the code extensively and developed new ways to extend the utilization series) and David Thipphavong (who did the initial programming and considerable experimentation).

[2] This draft is still in process and is incomplete. A spreadsheet with aggregate utilization-adjusted TFP is available from my web site, to be released in conjunction with the Fernald and Matoba (2009) FRBSF Economic Letter, on August 17, 2009. The investment- and consumption- TFP series, also discussed in this note, are likely to be made available after the September 2009 productivity release. By that time, the BEA is expected to have released all of the detailed NIPA tables following the July 2009 benchmark revisions, including those used in this project. Where necessary for the aggregate capital input data, the current version of the series splice together the pre- and post-revision data in 1995 in order to create a complete time series.

quality sources of aggregate and/or industry TFP, including the "multifactor productivity" measures produced by the Bureau of Labor Statistics (BLS), various measures produced by Dale Jorgenson and collaborators,[3] and the EU KLEMS project.

Most notably, these annual productivity measures control for heterogeneity across workers and types of capital. Consider labor input. Simple hours worked data (e.g., from the BLS productivity and cost release) combine hours of construction workers, fast-food cashiers, auto mechanics, dentists, engineers, CEOs, and so forth. These workers have very different wage rates which, presumably, correspond to differences in marginal products. Similarly, a computer (which provides a service flow for only three or four years) needs to have a higher marginal product than an office building (which might provide services for 50 years). These annual measures incorporate adjustments to weight different inputs using actual or estimated relative factor prices to control for these differences in implied marginal products.

Note that this heterogeneity in the data might matter even for researchers with interest in aggregate models with a representative agent and a single type of capital. For example, labor composition (or quality) fluctuates a fair amount at high frequency—e.g., in recessions, labor quality systematically rises, since workers with lower skills and education are more likely to lose their jobs. Unless measured TFP controls for labor composition then, relative to underlying technology, measured TFP will be biased up in recessions.

Economic theory suggests that another form of heterogeneity is potentially important: Heterogeneity by type of final product. Considerable recent literature has focused on so-called investment-specific technical change (see, for example, Greenwood, Hercowitz, and Krusell, 1997; and Basu, Fernald, Fisher, and Kimball, 2009). I use relative prices to decompose TFP for

---

[3] For references and available datasets, see
http://dvn.iq.harvard.edu/dvn/dv/jorgenson;jsessionid=5f474ccc4bb102aec4ff946761c8 (accessed August 12, 2009).

the aggregate economy into TFP for equipment and consumer durables, and into TFP for "consumption" (everything other than equipment and consumer durables).

As with the standard TFP residual, these measures are not necessarily good measures of technological change from quarter to quarter. Indeed, an important caveat is that Fisher (2006) and Basu, Fernald, Fisher, and Kimball (BFFK, 2009) find that pass-through from (fully corrected) relative technology shocks to relative prices is very slow. That said, uncorrected measures of TFP are more closely related to relative prices—almost as a measure of accounting.[4] BFFK still find the pass-through is not immediate, whereas we assume it is. But, importantly, we do not assume that TFP measures technology quarter-to-quarter. And we include an adjustment for utilization—the most important of those wedges between TFP and technology.

The adjustment for variable utilization in the quarterly series follows Basu, Fernald, and Kimball (2006). BFK sought to adjust for a range of non-technological factors that affect measured TFP, of which variations in the utilization margin–i.e., the intensity margin for the workweek of capital and labor effort—are only one. Other corrections include allowing for deviations from perfect competition and for various reallocation effects. BFK used annual data, where there are rich industry-level details on output and intermediate-input flows, as well as on industry investment. These data are not available quarterly. Nevertheless, the utilization-adjusted quarterly series is an improvement over more "naïve" measures of TFP as a high-frequency indicator of technological change.

Section I defines TFP, labor and capital inputs, and utilization. It discusses the method I follow to decompose TFP into investment and consumption components, and then discusses the BFK approach to controlling for variable utilization. Section II summarizes the key data sources

---

[4] The intuition comes from the dual approach to growth accounting: TFP can equivalently be defined as growth in real factor prices. If all firms faced the same factor prices and had the same factor shares, then real factor prices differ only because of output prices. See Basu, Fernald, Fisher, and Kimball (2009).

used to construct quarterly TFP. Section III provides a detailed discussion of data sources. Future drafts of this document will provide more discussion of the properties of the resulting series.

I. Method

Aggregate TFP

Suppose we model aggregate activity with an aggregate production function:

$$Y_t = F\left(Z_t \cdot K\left(K_{1,t-1}, K_{2,t-1}, ..K_{J,t-1}\right), E_t \cdot L\left(H_{1,t}, H_{2,t}, ...H_{N,t}\right), A_t\right)$$

K is capital input, which is an aggregate of the service flow, $K_{j,t-1}$, from the J types of capital (e.g., computers, transportation equipment, structures, and land); the service flow in period t is proportional to the stock of that type of capital at the end of period t-1. L is labor input, which is an aggregate of the hours worked, H_j, by N types of workers (e.g., female 40-year-old college-educated professionals, male 22-year old high-school dropouts, and so forth). Z is capital utilization (e.g., the average workweek of capital) and E is effort per unit of labor. A is technological change.

Suppose there is a representative firm that takes capital rental rates, R_j, and wages, W_n, as given and charges a markup μ of price over marginal cost. The first-order conditions for cost minimization imply that output elasticities are a markup over cost shares, i.e.,

$\left(\partial Y_t / K_{j,t}\right)\left(K_{j,t} / Y_t\right) = \mu\left(R_{j,t}K_j / P_t Y_t\right) = \mu\gamma_{j,t}$ and $\left(\partial Y_t / H_{n,t}\right)\left(H_{n,t} / Y_t\right) = \mu\left(W_n H_n / P_t Y_t\right) = \mu\beta_{n,t}$. $\gamma_{j,t}$ is the share of capital of type j, where $\sum_j \gamma_{j,t} = \alpha_t$, and $\beta_{n,t}$ is the share of labor of type n, where (with zero economic profits) $\sum_n \beta_{n,t} = (1-\alpha_t)$. In the data, we will take capital's share α_t as a residual, which enforces that capital and labor's shares sum to one. Note that, in this setup, differences in factor prices imply differences in marginal products.

Composition-adjusted growth in capital and labor input are:

$$\Delta \ln K_t \equiv \sum_j (\gamma_{j,t}/\alpha_t)\Delta \ln K_{j,t-1}$$

$$\Delta \ln L_t = \sum_n \left(\beta_{n,t}/(1-\alpha_t)\right)\Delta \ln H_{n,t} \equiv \Delta \ln Q_t + \Delta \ln H_t, \text{ where } \Delta \ln H_t = \Delta \ln \sum_n H_{n,t}$$

These definitions weight different types of inputs using marginal products. Markups hit all factors equally, so that they do not enter these definitions. Labor input is explicitly decomposed into raw hours worked, H, and "quality," Q, where Q is implicitly defined in the second equation as the difference between growth in labor input and growth in raw hours. The reason for explicitly breaking out quality and quantity of labor is that they come from different sources that rely on different methods. Differentiating the production function and dropping time subscripts (for simplicity) yields:

$$\Delta \ln Y = \mu(\alpha\Delta \ln K + (1-\alpha)\Delta \ln(L)) + \Delta \ln U + \Delta \ln A \tag{1}$$

where $\Delta \ln U \equiv \mu\left[\alpha\Delta \ln Z + (1-\alpha)\Delta \ln E\right]$. We normalize the elasticity of F with respect to technology, A, to equal unity.

We define TFP and utilization-adjusted TFP, $\Delta \ln A^{TFP}$, as:

$$\Delta \ln TFP \equiv \Delta \ln Y - \alpha\Delta \ln K - (1-\alpha)\Delta \ln L = \Delta \ln U + \Delta \ln A^{TFP} \tag{2}$$

$\Delta \ln A$ is thus utilization-adjusted TFP growth.

In the context of a specific model, TFP is often defined using (1), i.e., as the multiplicative technology term in the production function, A. Under standard conditions (constant returns to scale, perfect competition, and identical factor prices for all producers), the statistical definition corresponds to the multiplicative technology term in the model. Hulten (1978) shows that—in a model with heterogeneous, constant-returns, perfectly competitive producers facing identical factor prices—this definition of aggregate TFP corresponds to the outward shift in society's aggregate production possibilities frontier.

However, in some models (e.g., with markups, possibly heterogeneous across producers, of price above marginal cost, or with factor adjustment costs that lead the shadow cost of inputs to differ across firms), aggregate TFP and aggregate technology are not the same—even in the absence of variable factor utilization; see, for example, Basu and Fernald (2001). Even then, the statistical definition of $\Delta \ln TFP$ is still an object that can be defined in the model and compared with the data.

Any failures of aggregation (so that there is no aggregate production function of the form posited here) will, of course, show up in utilization-corrected TFP growth. Similarly, if observed factor shares do not equal output elasticities—as in the case with imperfect competition—then those effects will also show up in utilization-adjusted TFP growth. Using detailed industry data at an annual frequency, BFK control for these factors to develop a "purified" technology measure. As noted above, these necessary data are available only with a long lag, and are not available quarterly.

Investment versus consumption

Considerable recent literature looks at the role of "investment-specific technical change," as in Greenwood, Hercowitz, and Krusell (1997). Basu, Fernald, Fisher, and Kimball (2009) argue that a more natural (though equivalent) breakdown is along the lines of equipment investment versus consumption. To allow an analysis along these lines, I use relative prices to decompose aggregate TFP into TFP for the equipment-investment-sector and for the consumption-sector. "Consumption" in this context means everything other than equipment investment and consumer durables.

In particular, we can take aggregate TFP growth (defined in equation 1) as, identically, equal to:

$$\Delta \ln TFP = w^I \Delta \ln TFP^C + (1 - w^I)\Delta \ln TFP^C ,$$

where w^j is the share of sector j (consumption, C, or investment, I).[5] If producers in both sectors have equal factor shares, pay the same factor prices, and have indirect business taxes that are a constant proportion to one another,[6] then changes in relative TFP equal changes in relative prices:

$$\Delta \ln TFP^I - \Delta \ln TFP^C = \Delta \ln P_C - \Delta \ln P_I \qquad (2)$$

$\Delta \ln P_I$ is the prices of equipment and software combined with consumer durables; $\Delta \ln P_C$ is the price of business output less the price of investment.[7] That is, if $\Delta \ln P$ is growth in the price of business output, then $\Delta \ln P_C$ is defined implicitly by $\Delta \ln P = (1 - w^I)\Delta \ln P_C + w^I \Delta \ln P_I$.

I impose (2) quarter-by-quarter, which is a strong assumption. BFFK find that passthrough of relative changes in TFP to relative prices is not immediate, even in annual data. However, the link between relative TFP and relative prices is much closer than the link between relative *technology* and relative prices, where full pass-through takes three or more *years*. Much of the slippage, however, reflects margins such as utilization, which drive a gap between measured TFP and technology. We turn to utilization next.

---

[5] As Basu and Fernald (2002) discuss, there are also reallocation effects related to differences in factor prices across sectors. The data are not available to measure those terms in quarterly data, so we include them in sectoral TFP itself.

[6] Under zero profits, which we maintain, the value of output equals the value of input: $P^m Y^m = W^m L^m + R^m K^m$, where $m \subset (\text{Investment, consumption})$. Differentiating logarithmically, assuming equal factor shares in the two sectors, yields: $\Delta \ln Y^m - \alpha\Delta \ln K^m - (1-\alpha)\Delta \ln L^m = \alpha\Delta \ln R^m + (1-\alpha)\Delta \ln W^m - \Delta \ln P^m$. The left-hand-side is measured TFP; the right-hand-side is share-weighted real factor prices. Assuming factor prices are equal in the two sectors implies the equation in the text. Indirect business taxes drive a wedge between producer and purchaser prices but do not affect the relationship as long as log-changes over time are the same in both sectors. See Basu, Fernald, Fisher, and Kimball (2009) for more discussion of the relationship between relative prices and relative technologies.

[7] The price of business output less the price of BFI, $\Delta \ln P_C$, is defined implicitly by $\Delta \ln P = w^C \Delta \ln P_C + w^I \Delta \ln P_I$.

<u>Utilization</u>

Basu, Fernald, and Kimball (2006) seek to estimate "purified" Solow residuals by controlling for non-technological factors that could affect these residuals. In particular, BFK estimate a Hall (1990)-style regression on industry-level data, which allows for non-constant returns to scale and imperfect competition as well as variable factor utilization. In quarterly data, it is not possible to implement the full BFK estimation. However, we can implement part of it, in order to decompose TFP growth into utilization change, $\Delta \ln U$, and utilization-adjusted TFP, $\Delta \ln A^{TFP}$.

A large literature suggests that unobserved variations in factor utilization are important over the business cycle.[8] For example:

- Firms hoard labor in downturns, because they do not want to fire workers who have valuable skills that they will need in the future;
- firms reduce the workweek of capital, because it isn't worth paying a shift premium to get people to work at night or because the capital will depreciate as it is worked more intensively;
- firms shut factories because, in a putty-clay world, the value of the output that can be produced from using the capital doesn't cover the variable costs in terms of labor and materials.

The challenge is to derive a suitable proxy for unobserved output utilization variation, $\Delta \ln U$. BFK consider a firm that seeks to minimize the present discounted value of costs for any given path of output. There is a convex cost of adjusting the quasi-fixed factors—capital stock and number of employees. In addition to this extensive margin, firms have access to various intensive margins: Hours worked per employee; effort required of employees per hour of work; and the workweek of capital (e.g., varying the number of shifts). BFK show conditions in which the relatively easily observed margin (hours per worker) proxy for the two difficult-to-observe

---

[8] See Basu, Fernald, and Kimball (2006) for references.

margins (labor effort and capital's workweek). In particular, the basic idea behind using growth

in hours-per-worker to the regression as a proxy for unobserved variations in labor effort and

capital's workweek is that a cost-minimizing firm operates on all margins—whether observed or

unobserved—simultaneously. As a result, changes in observed margins can proxy for otherwise-

unobserved utilization changes. If labor is particularly valuable, for example, firms will work

existing employees both *longer* (observed hours per worker rise) and *harder* (unobserved effort

rises).

In particular, BFK estimate (with demand-side instruments) the following equation on

industry data:

$$\Delta \ln Y_i = \mu_i \Delta \ln X_i + \beta_i \Delta \ln(H^i / N^i) + \Delta \ln A_i$$

where

$$\Delta \ln X_i = s_{Ki} \Delta \ln K_i + s_{Li} \Delta \ln L_i + s_{Mi} \Delta \ln M_i.$$

X_i is revenue-share-weighted inputs of capital, labor, and intermediate-inputs, M_i.

$\ln(H^i / N^i)$ is hours/worker (note that total hours, as well as labor quality, is already included in

labor input, L_i). The coefficient β_i, which can be estimated, relates observed hours growth to

unobserved variations in labor effort and capital's workweek. That coefficient incorporates

various elasticities including, in particular, the elasticity of unobserved effort with respect to

hours, from the implicit function relating them (which came out of optimization).

To create a quarterly utilization series, we use the estimated industry β_i coefficients,

applied to quarterly data. We first detrend the data using the Christiano-Fitzgerald bandpass

filter to remove components of hours/worker at frequencies lower than 2 and exceeding 32

quarters. We then use the average industry weights from BFK to create an aggregate quarterly

utilization measure.

II. Data Sources

Key data sources for estimating (unadjusted) quarterly TFP for the U.S. business sector are the following:

(i) Output and hours: The BLS productivity and cost release provides data on $\Delta \ln Y$ and $\Delta \ln H$ for the business sector (which is what the quarterly capital data most closely correspond to). These data are available from 1947:1 on.

(ii) Capital input: The quarterly national income and product accounts (produced by the Bureau of Economic Analysis, BEA) provide investment data for 7 types of non-residential equipment, software, and structures. I use these data to create perpetual-inventory series on (end of previous quarter, i.e., beginning of current quarter) capital stocks by different type of asset. Weighting growth in these disaggregated types of capital with estimated factor payments (which, in turn, use estimated user costs) gives quarterly capital input $\Delta \ln K$.

(iii) Factor shares: I interpolate the annual data on factor shares, α and (1- α), from the BLS multifactor productivity database.[9]

(iv) Labor composition: From 1979:1 on, I use estimates that follow Aaronson and Sullivan (2001), as updated by Bart Hobijn and Joyce Kwok. Prior to 1979, I interpolate and extrapolate annual data from BLS multifactor productivity data.

(v) Investment versus consumption technology: To decompose aggregate TFP along final demand lines, I create two Tornquist price indices from NIPA data. The first is the price of "equipment," defined as equipment, software, and consumer durables. The second is the price of non-durable "consumption," defined as the

---

[9] Results were little affected in experiments with other reasonable choices, such as using national accounting data.

price of business output less the price of equipment (which, of course, comprises equipment, software, and consumer durables). I assume the relative price of equipment investment corresponds, quarter-by-quarter, to TFP in consumption relative to equipment investment. This measure of relative TFP is not, of course, necessarily equal to technology change period by period.

To estimate a quarterly series on utilization, the key data source is the following:

(vi)   Industry and aggregate utilization: Hours-per-worker (H^i / N^i) by industry from the monthly employment report of the BLS. These are used to estimate a series on industry utilization $\Delta \ln U_i = \beta_i \Delta \ln(H^i / N^i)$, where β_i is a coefficient estimated by BFK. I then calculate an aggregate utilization adjustment as $\Delta \ln U = \sum_i w_i \Delta \ln U_i$, where w_i is the industry weight from BFK (taken as the average value over the full sample).[10]

(vii)   Investment and consumption utilization: I use input-output data from Basu, Fernald, Fisher, and Kimball (2009). They suggest that a reasonable measure of equipment investment utilization change is

$$\Delta \ln U^I = [b_{J,1} \quad b_{J,2} \quad ...]'[I - B]^{-1}[\Delta \ln U_1 \quad \Delta \ln U_2 \quad ...]':$$

- $[b_{J,1} \quad b_{J,2} \quad ...]$ is a row vector of commodity shares of equipment investment and consumer durables. For example, if commodity 1 were electrical equipment, then $b_{J,1}$ would be the share of electrical equipment in total equipment investment and consumer durables).
- B is the intermediate-input shares from the use matrix (where element b_{ij} is the share of commodity j in industry i).
- $[\Delta \ln U_1 \quad \Delta \ln U_2 \quad ...]'$ is the vector of industry utilization changes.

---

[10] $w_i = w_i^Y / (1 - s_{Mi})$, where w_i^Y is the industry's weight in aggregate value added, and s_{Mi} is the share of intermediate inputs.

For the industry weights, $[b_{J,1} \quad b_{J,2} \quad ...]'[I - B]^{-1}$, I use the average value over the BFFK sample of 1961-2004. Consumption ("other") utilization is implicitly defined by the assumption that total utilization change is a share-weighted average of utilization in equipment investment and consumption, so that

$$\Delta \ln U^C = \left(\Delta \ln U - w^I \Delta \ln U^I \right) \big/ (1 - w^I).$$

As described in the next section on details of implementation, several other data sources are used in constructing the quarterly series. These include several series that are interpolated—and, for the most recent periods, extrapolated—from annual estimates of the BLS (e.g., labor quality and inputs of land). They also include industry weights that were used by BFK to aggregate the industry utilization series.

As already noted, the resulting series differs conceptually from the BFK purified technology series along several dimensions. BFK use detailed industry data to construct estimates of industry technology change that control for variable factor utilization and deviations from constant returns and perfect competition. They then aggregate these residuals to estimate aggregate technology change. Thus, they do not assume the existence of a constant-returns aggregate production function. The industry data needed to undertake the BFK estimates are available only annually, not quarterly. As a result, the quarterly series estimated here does not control for deviations from constant returns and perfect competition.[11]

As BFK (and, earlier, Basu and Fernald, 1997) argue, even if the typical industry has close to constant returns, there is substantial heterogeneity across industries, and this heterogeneity generates reallocation terms that have aggregate implications and that affect

---

[11] The output data also differ, both in vintage and data source, from the annual data used by BFK.

estimates of aggregate dynamics. The quarterly series here does not control for these aggregate

reallocation terms.

III. Details on Data and Variable Construction

Labor Productivity

The main source for the quarterly TFP series is business-sector labor productivity data

produced by the BLS each quarter. The data begin in 1947:1, and new data are available

approximately five weeks after the end of each quarter. At that point, it is possible to produce an

estimate of the quarterly TFP series. The BLS itself produces an <u>annual</u> TFP series, but only

with a lag of several years.

Factor Shares

We need relative shares in revenue for labor and capital. I interpolate the annual shares

reported in the BLS multifactor productivity dataset (using a cubic spline). Those data begin in

1948. For quarters before and after the multifactor-productivity data are available, I assume the

annual shares are unchanged from their first/last value before implementing the cubic spline.

(The series has relatively modest variation, so this assumption is likely to be innocuous.) [12]

In principle, one could estimate the quarterly factor shares from national accounting data.

There are several challenges in trying to calculate the shares properly from national-accounting

data alone. First, we need to decompose proprietor's income into labor and capital income.

With national accounts data, we could assume that the factor shares are the same as for non-

proprietors. Alternatively, we could go beyond national accounting data, as both the BLS (for

---

[12] If implicit contracts are important, then the observed fluctuations in factor payments might not reflect actual fluctuations. Indeed, the business-cycle fluctuations in factor shares might not be allocative at all, arguing for simply assuming Cobb-Douglas and using constant factor shares.

their multi-factor-productivity data) and Jorgenson do, and impute a wage to proprietors based on their observed demographic characteristics in the Current Population Survey. The latter method is probably more appropriate, but requires detailed data and computation to implement.

Second, business taxes are a challenge. Define *PY* as nominal business-sector GDP, which is measured using market prices, i.e., from the point of view of purchasers. For factor shares, we need revenue from the point of view of the producer. Let TPS be taxes on production less subsidies (this replaces the former name, indirect business taxes). We want to exclude sales and excise taxes, which are not a payment to a factor. We <u>do</u> want to include motor vehicle and property taxes, which are part of the cost of using capital. And we want to include subsidies, which are revenue to the producer.

On an annual basis, the BEA (NIPA Table 3.5) provides the components of taxes on production. Unfortunately, for these purposes, property taxes include the property taxes of owner-occupied housing, since the BEA considers that a "business" (though owner-equivalent rent is not included in business output in the BEA's sectoral decomposition of GDP).

In any case, it is a bit of a challenge to get all the pieces to calculate factor shares quarterly. Interestingly, taking *PY-TPS* provides a reasonably good approximation in annual data to factor-cost in the BLS MFP data. When necessary to calculate the implied interest rate (needed for the cost of capital, below), I use this value as an approximation to total factor cost. That said, capital-input measures do not appear too sensitive to reasonable variation for the value of nominal capital payments used to compute the implicit nominal interest rate.

Capital Input

We have to aggregate heterogeneous capital goods into a capital-input (or capital services) measure, *K.* I use quarterly estimates of the stocks of nine types of capital, including

six categories of equipment and software, plus structures, inventories, and land. For equipment, software, and structures, I use detailed investment data, I_j, with assumed (annual) geometric depreciation rates, δ_j, in parentheses:[13]

(1) Computers and peripheral equipment (31.5 percent);

(2) Software (44 percent)

(3) Other information processing equipment[14] (13.3 percent)

(4) Industrial equipment (9.3 percent);

(5) Transportation equipment (12.8 percent);

(6) Other equipment (13.9 percent);

(7) Structures (2.4 percent).

For inventories (with a depreciation rate of 0 percent), I use direct estimates of the quarterly stocks from NIPA. For land, I interpolate the annual values from the BLS multifactor productivity dataset.

For the categories of equipment and software and for structures, I calculate beginning-of-quarter (end of previous quarter) capital stocks $K_{j,t-1}$ using the perpetual inventory method, so that $K_{j,t-1} = (1-\delta_j)K_{j,t-2} + I_{j,t-1}$. As an initial estimate of the capital stock, I use end-of-year BEA estimates of the stock of each type of capital as of the end of 1946 (i.e., beginning of 1947:1).

---

[13] For equipment and structures, I obtain these investment data from NIPA Tables 1.5.5 (nominal) and 1.5.6 (chain-weighted). This level of disaggregation allows a consistent time series since the 1940s. It is possible to obtain more detailed quarterly investment data, but generally for a shorter sample period. The depreciation rates come from Fraumeni (1997), who provides estimates of geometric depreciation rates for 31 types of equipment and 15 types of structures. (We use Bureau of Economic Analysis, 2004, for medical and nonmedical instruments.) We aggregate to the level of four types of equipment and one type of structure using as weights the estimated nominal value of the stock of capital of each detailed type. For inventories, the data come from NIPA Tables 5.7.5A, 5.7.5B, 5.7.6A, and 5.7.6B.

[14] Other includes communication equipment, medical equipment and instruments, nonmedical instruments, photocopy and related equipment, and office and accounting equipment.

According to the BLS, land accounts for approximately 11 percent of capital income in the business sector.[15] I interpolate the annual estimates from the BLS MFP database. After the end of the BLS sample, I extrapolate assuming the annual values follow an AR(1) process). Since land use is a smooth and slow moving series, the approximation error from the interpolation is likely to be small.

I assume that capital input of a particular type of capital is proportional to $K_{j,t}$, the stock of that type of capital as of the beginning of the quarter. (With annual data, it is common to assume that capital input is the average of the capital stock in years t-1 and t. This mid-period convention seems less appropriate for quarterly data.)

To go from disaggregated capital stocks to a composite capital input measure, the standard first-order conditions for firm optimization imply that we need to weight by service flows. Implicitly, the nominal value of the service flow from a given type of capital j depends on the user cost R_j of that type of capital multiplied by the stock of that type of capital, i.e., $R_j \cdot K_i$.

Standard first-order conditions for capital imply that the user cost is $R_{jt} = (i_t + \delta_j - \pi^e_{jt+1})P^I_{jt}$, where i is the nominal interest rate, π^e_{jt+1} is the expected rate of price appreciation for asset j between today and next period, and P^I_j is the purchase price (investment price) for asset j.

Given an estimate of the user costs, the Tornquist index of the service flow from aggregate capital input is defined as:

$$\Delta \ln K = \sum_j \frac{[s_j(t) + s_j(t-1)]}{2} \cdot \Delta \ln K_j$$

where the nominal shares in each period are $s_j = \dfrac{R_j \cdot K_j}{\sum_j (R_j \cdot K_j)} = \dfrac{(r + \delta_j - \pi_j^e) \cdot P_j^I \cdot K_j}{\sum_j (r + \delta_j - \pi_j^e) \cdot P_j^I \cdot K_j}$.

To calculate the user cost, we need measures of expected asset-specific price appreciation π_{jt+1}^e as well as nominal interest rate series. For expected price appreciation, I experimented with several methods. To start, suppose we assume rational expectations. Then actual inflation (between periods t and $t+1$) should equal ex ante expected inflation plus white noise error. This reasoning suggests that it should be reasonable to use actual asset inflation as our estimate of expected inflation. Unfortunately, since ex post asset inflation is sometimes extremely volatile, this measure leads to implausibly volatile shares s_J from quarter to quarter. As another approach, I estimated a simple univariate autoregressive forecasting model of the asset price and used the fitted values. This led to smoother shares, but had the undesirable feature that the forecasting model changed each time the data was updated—leading to minor but undesirable revisions in capital input over the historical period. Moreover, it is implausible that agents knew the full-period model; and using a recursive method (i.e., where only observations up through period t were used to forecast asset inflation for period $t+1$) implied having very few observations in the early years.

As a compromise, which led to a priori reasonable results, I estimated expected asset-price inflation using a centered 16-quarter moving average of price changes.[16] This approach weights the recent past equally with the actual (unknown, but expected) future and has the a priori desirable property that asset weights s_J are relatively smooth from quarter to quarter. At the same time, these weights retain the genuine low-frequency movements, e.g, the shift towards information technology over time.

---

[16] At the end of the sample, I drop the future observations since they are obviously not observed.

For the nominal interest rate, suppose we take the assumption of zero profits literally, so that all residual factor payments go to capital. There is then some implicit rate of return i such that the sum of factor payments is equal to output. As a residual, capital compensation is $P_K K = \alpha(PY - TPS)$. This compensation, in turn, equals the sum of payments to the different types of capital: $K_{comp} = \sum_j R_j \cdot K_{input,j} = \sum_j (i + \delta_j - \pi_j) \cdot P_j^I \cdot K_j$. This equation implicitly defines the nominal interest rate i: $K_{comp} = i \cdot \sum_j P_j^I \cdot K_j + \sum_j (\delta_j - \pi_j) \cdot P_j^I \cdot K_j$, or

$$ i = \frac{K_{comp} - \sum_j (\delta_j - \pi_j) \cdot P_j^I \cdot K_j}{\sum_j P_j^I \cdot K_j} . $$

Once we have a measure of the nominal interest rate i, we can calculate the user costs and relative weights for each of the types of capital. We can then calculate the growth in the index of capital input, giving us the key information necessary to map quarterly labor productivity into quarterly TFP.

Utilization

The disaggregated BLS hours-per-worker data necessary to make the BFK adjustment are available quarterly (or even monthly), matching our needs. I assume that the coefficients on hours-per-worker growth, at a quarterly frequency, match the annual BFK coefficients. This allows me to estimate a quarterly utilization adjustment that, when annualized, is extremely close to the BFK adjustment.[17]

---

[17] There are some nevertheless some differences. For example, in some cases, BLS data are not available for the full sample period or for all detailed industries; in those cases, BFK augmented the BLS data with annual estimates provided by Dale Jorgenson. Those data are not available quarterly, necessitating different adjustments. Nevertheless, the utilization estimate is extremely close to the BFK estimate.

There are a number of technical details. First, we need a full panel of estimates of industry hours per worker. This requires merging BLS data on hours per worker on an SIC basis (which were discontinued in April, 2003) with more recent data on a NAICS basis. The BFK estimates used SIC classifications, so we generally use the NAICS data to extrapolate the SIC data beyond 2002. We also need to estimate some series for the earlier years. In particular, the SIC data for construction and manufacturing industries are generally available as of 1947 (sometimes earlier); much of the non-manufacturing, non-construction data begin only in 1964 or, in some cases, even later. BFK-augmented values that aren't available from the BLS with annual data from Dale Jorgenson; since these data are not available quarterly, we instead use the available industry data to extrapolate series backwards. More specifically:

- In the BLS data, hours data for both instruments and electrical equipment begin only in 1988; from 1988-2003, the correlation of hours in industrial machinery with hours in electrical equipment is above 0.9, and the correlation with instruments is above 0.8. Hence, for the 1988-2003 period, I project hours per worker in both electrical equipment and in instruments on hours per worker in industrial machinery, and then use the fitted values back to 1947. In addition, there is also no separate instruments industry in the NAICS data (it is part of electronics), so we extend the instruments category with data on computer and electronic products.

- For transportation, information (i.e., communications), and utilities, there are disaggregated NAICS data back to either 1964 or 1972, but only aggregated SIC data back to 1964. In those cases, we take the NAICS data as our primary dataset and backcast with the SIC data.

- Even on an SIC basis, data for most service industries begin only in 1964. We extract

  three principal components from the construction and manufacturing industries (22

  total industries), and then project service hours on these principal components. For

  the earlier period, the fitted values from these projections provide an estimate of

  quarterly hours per worker for all industries.

Second, I bandpass filter the log of the quarterly hours-per-worker data by industry to

obtain frequencies between 8 and 32 quarters, I then take first differences and multiply by the

estimated industry utilization coefficient from BFK. This gives industry estimates of utilization

change. I use annual weights from BFK to aggregate across industries. For the period before

1949, I use the 1949 values; similarly, after 1996, I use the 1996 values.[18]

Third, we use coefficients estimated in BFK to create an industry utilization series.

Finally, we use annual BFK industry weights to aggregate.

IV. Comparison to the BLS MFP data

The chart below shows the annualized growth rate in the quarterly series is very close to

the growth in the BLS Multifactor Productivity measure for the business sector.[19] The BLS

measure is only available annually. The minor differences arise from four main sources:

(i)   The quarterly series incorporates the 2009 benchmark revisions, which revised

        down annual output growth in 2008 by about 0.8 percentage point. In addition,

---

[18] BFK bandpass filter annual rather than quarterly data, which leads to a slight difference in the estimated trend and, hence, in the estimated utilization series.

[19] Note that annualizing the quarterly series is *not* the same as averaging the four quarterly growth rates, which would create a Q4/Q4 measure. Instead, I took the seven quarter moving average of growth rates with "tent weights", where the weights from Q2 of year *T-1* to Q4 of year *T* are 1/16, 2/16, 3/16, 4/16, 3/16, 2/16, 1/16. It is readily verified numerically that this is very close to summed the quarterly growth rates to create a log-levels index; taking exponents to create a level; averaging the levels during the four quarters of each year; and then taking growth rates of this annual levels index.

the new data led to upward revisions to capital input growth in recent years, which further revises down TFP growth.

(ii)   The BLS and Hobijn-Kwok estimates of labor quality differ somewhat. For 2008, the differences are quite stark: The BLS estimates that labor quality was flat, whereas the Hobijn-Kwok index rose about 0.9 percent.

(iii)   The quarterly capital input measure uses less-disaggregated investment data. In addition, the perpetual inventory method is applied quarter-by-quarter rather than annually, which leads to some small differences.

(iv)   The hours data differ between the BLS MFP data and the BLS quarterly productivity-and-cost data, and I use the latter.
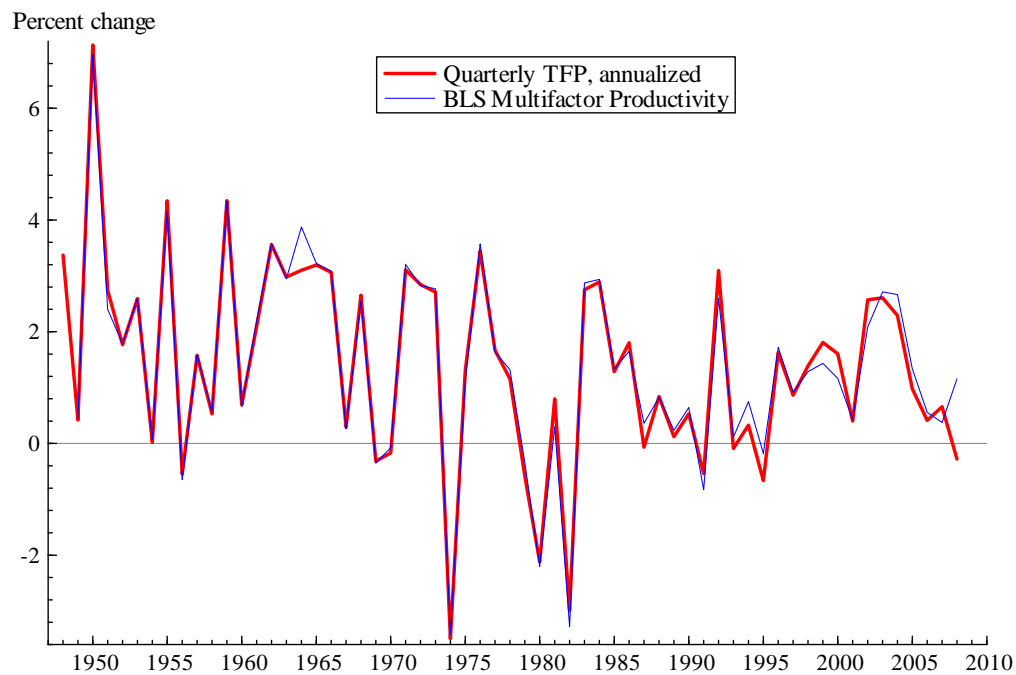
References

Basu, Susanto, John Fernald, and Miles Kimball (2006). "Are Technology Improvements Contractionary?" *American Economic Review*.

Basu, Susanto, John Fernald, Jonas Fisher, and Miles Kimball (2009). "Sector-Specific Technical Change." Manuscript

Bureau of Economic Analysis (2004). "BEA Depreciation Estimates." Downloaded from www.bea.gov/national/FA2004/Tablecandtext.pdf.

Bureau of Labor Statistics (2009). "Historical multifactor productivity measures (SIC 1948-87 linked to NAICS 1987-2008)." *ftp://ftp.bls.gov/pub/special.requests/opt/mp/prod3.mfptablehis.zip* (downloaded June 26, 2009.)

Fisher, Jonas D.M.(2006) . "The Dynamic Effects of Neutral and Investment-Specific Technology Shocks," *Journal of Political Economy*, University of Chicago Press, vol. 114(3), pages 413-451, June

Fraumeni, Barbara M. (1997). "The Measurement of Depreciation in the U.S. National Income and Product Accounts." *Survey of Current Business,* July.

Greenwood, Jeremy , Zvi Hercowitz and Per Krusell (1997). "Long-Run Implications of Investment-Specific Technological Change." *The American Economic Review*, Vol. 87, No. 3 (Jun., 1997), pp. 342-362.

Hulten, Charles R. (1978). "Growth Accounting with Intermediate Inputs," *Review of Economic Studies*, Vol. 45, No. 3, October 1978, pp. 511-518.