NBER WORKING PAPER SERIES

THE IMPACT OF PLANT-LEVEL RESOURCE REALLOCATIONS AND TECHNICAL PROGRESS ON U.S. MACROECONOMIC GROWTH

Amil Petrin
T. Kirk White
Jerome P. Reiter

Working Paper 16700
http://www.nber.org/papers/w16700

NATIONAL BUREAU OF ECONOMIC RESEARCH
1050 Massachusetts Avenue
Cambridge, MA 02138
January 2011

The research in this paper was conducted while the authors were Special Sworn Status researchers of the U.S. Census Bureau at the Triangle Census Research Data Center. Any opinions and conclusions expressed herein are those of the authors and do not necessarily represent the views of the U.S. Census Bureau or the National Bureau of Economic Research. All results have been reviewed to ensure that no confidential information is disclosed. We thank Bert Grider and Arnie Reznek for many disclosure avoidance reviews and the editor and referee for very helpful comments. We also thank numerous seminar participants for many helpful comments.

The Impact of Plant-level Resource Reallocations and Technical Progress on U.S. Macroeconomic Growth
Amil Petrin, T. Kirk White, and Jerome P. Reiter
NBER Working Paper No. 16700
January 2011
JEL No. E32,L6,O47

ABSTRACT

We build up from the plant level an "aggregate(d)" Solow residual by estimating every U.S. manufacturing plant's contribution to the change in aggregate final demand between 1976 and 1996. Our framework uses the Petrin and Levinsohn (2010) definition of aggregate productivity growth, which aggregates plant-level changes to changes in aggregate final demand in the presence of imperfect competition and other distortions/frictions. We decompose these contributions into plant-level resource reallocations and plant-level technical efficiency changes while allowing in the estimation for 459 different production technologies, one for each 4-digit SIC code. On average we find positive aggregate productivity growth of 2.2% in this sector during this period of declining share in U.S. GDP. We find that aggregate reallocation made a larger contribution to growth than aggregate technical efficiency. Our estimates of the contribution of reallocation range from 1.7% to 2.1% per year, while our estimates of the average contribution of aggregate technical efficiency growth range from 0.2% to 0.6% per year. In terms of cyclicality, the aggregate technical efficiency component has a standard deviation that is roughly 50% to 100% larger than that of aggregate total reallocation, pointing to an important role for technical efficiency in macroeconomic fluctuations. Aggregate reallocation is negative in only 3 of the 20 years of our sample, suggesting that the movement of inputs to more highly valued activities on average plays a stabilizing role in manufacturing growth. Our results have implications for both the theoretical literature on growth and alternative indexes of aggregate productivity growth based only on technical efficiency.

Amil Petrin
Department of Economics
University of Minnesota
4-101 Hanson Hall
Minneapolis, MN 55455
and NBER
petrin@umn.edu

T. Kirk White
Economic Research Service, USDA
1800 M St., NW
Washington, DC 20036
tkirkwhite@gmail.com

Jerome P. Reiter
Duke University
jerry@stat.duke.edu

1 Introduction

What are the micro-level components of aggregate productivity growth? Aggregate final demand can increase without an increase in input use if plants become more technically efficient, perhaps by inventing new and better methods of production or by learning to imitate other better-performing plants. Final demand can also increase without more input use if inputs reallocate to more valued market activities. Theoretically, the two stories – technical efficiency and reallocation – are not mutually exclusive, and both may be important causes of aggregate productivity growth (APG) at business cycle frequencies and in the long run.

In this paper we construct estimates of every U.S. Manufacturing plant's contribution to changes in APG between 1976 and 1996. There are a wide variety of such definitions using plant-level data. Our contribution is to be the first to adopt the one from Petrin and Levinsohn (2010), which insists that changes at the micro-level in reallocation and technical efficiency aggregate to the change in final demand holding labor and capital constant.

Using U.S. Census data and the Annual Survey of Manufacturers to estimate this "aggregate(d) Solow residual," we find an average annual rate of growth over this period of 2.2%. Over this same period manufacturing's share of U.S. GDP falls from 21% to 15%. Thus either plant-level technical efficiency or a reallocation across plants of inputs (or both) led U.S. manufacturing to positively contribute to growth in the face of its declining share in U.S. output.

We investigate the role of aggregate reallocation and aggregate technical efficiency in APG. The growth rate of aggregate technical efficiency is the Domar-weighted sum of plant-level growth rates in technical efficiency, where this Domar weight is equal to plant-level revenue divided by aggregate value added. Aggregate reallocation under this definition tracks the movement of inputs across plants, increasing when an input moves from a lower-valued to higher-valued activity. In total each plant contributes one term related to the plant's technical efficiency change and five terms - one for each input we consider - related to aggregate reallocation.

Estimators of the plant-level contributions to these quantities require production function estimates. We exploit the micro-level data, relaxing the usual assumption of the existence of one aggregate manufacturing economy-wide production function. Specifically, we allow for different production functions for each of our 459 4-digit SIC industries, estimating parameters for each industry separately. In the estimation we are also flexible on the approach, estimating the production functions parameters with a variety of estimators robust to different econometric problems, including the use of Ordinary Least Squares, Levinsohn and Petrin (2003, LP), and the Wooldridge (2009) variant of the LP estimator (programs are publicly available).

In explaining APG over the two decade period we find that reallocation contributes positively on average and serves to stabilize the overall level of growth in the declining manufacturing sector. Specifically we find that aggregate reallocation's contribution to this growth is positive in all but 3 years, on average accounting for more than half of aggregate productivity growth (1.7% to 2.2% per year, depending on the production function estimator). The volatility in the reallocation term is relatively small, with the standard deviation of 1.1% to 1.7%. In contrast, technical efficiency growth in this declining industry was smaller on average (0.2% to 0.6% per year), and was also responsible for most of the volatility in aggregate productivity growth, as its standard deviation was 2.6% to 3.0%.

The APG decomposition and our data allow us to decompose aggregate productivity at any level of aggregation. We show that the patterns we found for the entire manufacturing sector generally also hold at the 2-digit SIC industry level: for most industries the average contribution of reallocation is greater than the average contribution of technical efficiency growth, and technical efficiency growth is significantly more volatile than growth from reallocation. We find that for most industries that the contribution of reallocation is positive in almost all years. We also find significant variation across industries in the relative contributions of reallocation and technical efficiency growth.

The result that aggregate reallocation makes relatively stable and mostly positive contributions to aggregate productivity growth is robust to a variety of estimators of plant-level productivity, and has been found in Chilean and Colombian data as well. This result makes economic sense, as Petrin and Levinsohn (2010) show that in the presence of imperfect competition, frictions in input markets, or fixed costs, reallocation of resources can contribute to aggregate productivity growth. Furthermore, we expect that any market populated by profit-maximizing firms will have resources reallocating on average towards uses with higher marginal products.

On reallocation, to the extent that an economy is not perfectly frictionless or perfectly competitive, policies that reduce these frictions or increase competition may have large effects on aggregate productivity growth via reallocation. Many of these policies relate to specific inputs, like labor or capital. Our estimation approach recovers one term per plant for each input and we decompose aggregate reallocation into terms including production workers, non-production workers, capital, and intermediate inputs to try to understand where frictions may be most important in U.S. manufacturing.

These results are useful for determining which of the many theoretical growth models with adjustment frictions appear consistent with U.S. manufacturing. For example, in Melitz (2003) there is no growth in plant-level technical efficiency as the only source of aggregate productivity growth comes from reallocation. When exposed to trade resources move from the low productivity to the high productivity plants, so productivity (which is isomorphic to technical efficiency) is a sufficient plant-level statistic for tracking plant-level reallocation. Our setup allows for plant-level productivity growth and for a reallocation term for each input at each plant. We find a significant role for reallocation in growth, which is consistent with Melitz (2003), However, we find its role varies across inputs and that the inputs do not necessarily track plant-level technical efficiency movements well. We also find that half of growth is related to plants become more technically efficient themselves.

Our results shed light on the precise meaning of counterfactuals that take the U.S. as a "frictions benchmark" and then ask how much output would increase if a country were able to achieve the U.S. level of frictions. For example, Hsieh and Klenow (2009) ask what the impact for growth would be in China and India if capital and labor were reallocated to reflect the level of frictions that we see in U.S. manufacturing industries. Our findings suggest that the U.S. benchmark is one with small gains from further reallocation of non-production and production workers, and substantially larger gains from the reallocation of capital.

Several recent models of growth have no channel for growth via intermediate inputs. Our results show that the large role of intermediates in production of manufacturing leads to a large role for reallocation growth for intermediate inputs in aggregate U.S. manufacturing productivity growth. We show this finding suggests that models of growth or cyclicality that assume the existence of a valued-added production function in an economy with perfect competition and no frictions or distortions attribute too much growth to the direct effect of technology shocks.

While the finding of a positive contribution of aggregate reallocation makes economic sense, it is in contrast to estimates of productivity growth due to reallocation as defined by other measures, such as in Baily, Hulten, and Campbell (1992, BHC hereafter). These indices define APG exclusively as the change in the average of the plant-level technical efficiency shocks, and thus do not aggregate plant-level changes in inputs and technical efficiency to changes in aggregate value added. Petrin and Levinsohn (2010) explain how the BHC index is related to APG. When we estimate aggregate productivity growth and reallocation as defined by the BHC index, we find that the volatility of growth due to reallocation is enormous: the standard deviation of the annual rate is as high as 7.8 percentage points – more than 4 times the volatility of the APG measure of reallocation. In many years, the contribution of BHC-measured reallocation is both large (in absolute value) and negative, sometimes indicating a decline of more than 20% in a single year. We find these results are robust to a variety of production function estimators, suggesting the way one defines aggregate productivity growth can have a substantial impact on how one interprets the roles of technical efficiency and reallocation in any economy. These differences between APG-measured reallocation and BHC-measured reallocation for U.S. manufacturing data are also consistent with findings for Chilean, Colombian, and

Japanese micro data.

In section 2 we discuss the theory in .15 time. Section 3 describes the discrete-time approximation. Section 4 describes the estimation. Section 5 describes the data. Readers interested only in the results can skip to section 6. Section 7 concludes.

2 Theory

Measuring aggregate productivity growth is an old and honored tradition in economics and there is an enormous theoretical and empirical literature devoted to it. Solow (1957) shows that in a perfectly competitive economy with an aggregate production function and without distortions, the (Solow) production function residual measures both aggregate technology change and aggregate productivity growth (APG), which is equal to the change in aggregate final demand. Hulten (1978) examines the case when (different) sectoral level production functions exist but the setting remains competitive and without distortions. He finds that the sectoral production function residuals, when properly weighted, exactly aggregate to APG. In both of these cases, there is no further role for the reallocation of resources in APG as all inputs are chosen so that value of an input's marginal product is equal to its marginal price.

Hall (1988) and Hall (1990) show that the estimate of technological change is affected by imperfect competition. More recently, Basu and Fernald (2002) study an economy with markups, showing that APG and aggregate technological progress differ because markups drive a wedge between marginal products, which leads to possible role for reallocation of resources in increasing APG and aggregate final demand.

Petrin and Levinsohn (2010) extend Basu and Fernald to plant-level data, showing how to aggregate changes in plant-level technical efficiency and changes in resource allocations across plants to changes in aggregate final demand. The linkage provides a theoretical basis for decomposing changes in aggregate final demand holding primary inputs constant into the contribution of technological progress (or "technical efficiency") and several terms that measure the contribution of the reallocation of inputs across plants, one for every input. In this paper we provide the first application of the Petrin and Levinsohn (2010) decomposition of APG to U.S. data (P-L hereafter).

We operate in continuous time and assume the production side of the economy has at any time at most N plants. While it is not difficult to extend the framework to multi-product plants, we assume for transparency all plants are single product plants. Every plant may have a different production technology, and we let each plant i's production technology be written as

$$Q^i(X_i, M_i, \omega_i), \tag{1}$$

where $X_i = (X_{i1}, \ldots, X_{iK})$ is the vector of K primary input amounts used at plant i, $M_i = (M_{i1}, \ldots, M_{iJ})$ is the vector giving the amount of each plant j's output used as an intermediate input at plant i, and ω_i is the level of plant i's technical efficiency. Primary inputs may include several different types of labor and capital, and any of the N products may potentially be used as an input in production somewhere in the economy.

We use F_i to denote the sum of all fixed and sunk costs that are paid by plant i. We normalize these costs to the equivalent of the forgone output and deduct them directly from the production function, letting

$$Q_i = Q^i(X_i, M_i, \omega_i) - F_i. \tag{2}$$

The total amount of output from plant i that goes to final demand Y_i is then

$$Y_i = Q_i - \sum_j M_{ji},$$

where $\sum_j M_{ji}$ is the total amount of i's output that serves as intermediate input within the plant and at other plants. The differential in levels is

$$dY_i = dQ_i - \sum_j dM_{ji},$$

P_i denotes the price of plant i's output, and thus $\sum_i P_i dY_i$ is equal to the change in final demand.

Aggregate productivity growth is then defined as the difference between the change in aggregate final demand and the change in aggregated expenditures on primary inputs:

$$APG \equiv \sum_i P_i dY_i - \sum_i \sum_k W_{ik} dX_{ik}, \tag{3}$$

where W_{ik} equals the unit cost of the kth primary input and dX_{ik} is the change in the use of that primary input at plant i. Converting (3) to growth rates we have:

$$APG_G = \sum_i D_i dlnY_i * - \sum_i \sum_k c_{ik} dlnX_{ik}, \tag{4}$$

where $D_i = \frac{P_i Q_i}{\sum_{i=1}^N P_i Y_i}$ is the .15 (1961) weight, $dlnY_i * = \frac{dY_i}{Q_i}$ is the growth rate of i's output going to final demand, and

$$c_{ik} = \frac{W_{ik} X_{ik}}{\sum_{i=1}^N P_i Y_i}.$$

We do not observe in the data the amount of a plant's output that ultimately goes to final demand. However, the Growth Accounting Identity shows that aggregate final demand is equal to aggregate value added:

$$\sum_i D_i dlnY_i * = \sum_i D_i^v dlnVA_i$$

with value added

$$VA_i = P_i Q_i - \sum_j P_j M_{ij} \tag{5}$$

and the .15 weight equal to the plant's share of value added $D_i^v = \frac{VA_i}{\sum_i VA_i}$. We then replace the first term in (3) and calculate aggregate productivity growth as

$$APG_G = \sum_i D_i^v dlnVA_i - \sum_i \sum_k c_{ik} dlnX_{ik}. \tag{6}$$

where we note we can rewrite

$$c_{ik} = \frac{W_{ik} X_{ik}}{\sum_i VA_i}$$

dividing through instead by aggregate value added.

Lemma 1 in P-L shows when Q_i is differentiable equation (3) can be decomposed as follows:

$$\sum_i \sum_k (P_i \frac{\partial Q_i}{\partial X_k} - W_{ik}) dX_{ik} + \sum_i \sum_j (P_i \frac{\partial Q_i}{\partial M_j} - P_j) dM_{ij} - \sum_i P_i dF_i + \sum_i P_i d\omega_i, \tag{7}$$

where $\frac{\partial Q}{\partial X_k}$ and $\frac{\partial Q}{\partial M_j}$ are the partial derivatives of the output production function with respect to the kth primary input and the jth intermediate input respectively, dM_{ij} is the change in intermediate input j at plant i, dF_i is the change in fixed and sunk costs, and $d\omega_i$ is the change in "net output" at plant i, defined as the output remaining after the contribution of both primary and intermediate inputs at plant i have been deducted:

$$d\omega_i = dQ_i - \sum_k \frac{\partial Q_i}{\partial X_k} dX_{ik} - \sum_j \frac{\partial Q_i}{\partial M_j} dM_{ij}. \tag{8}$$

Equation (7) shows that under this definition of aggregate productivity growth, if at every firm every marginal product is equated with every marginal cost, then further reallocation cannot increase growth, as all allocative efficiency gains have been achieved. However, if there is market power (i.e. markups) or frictions such as adjustment costs or taxes, or other characteristics of the economy that lead to a divergence between the marginal product and the marginal cost, then a reallocation of inputs alone can increase aggregate productivity growth. This reallocation effect is captured in the first two summation terms in (7).

Equation (7) can be rewritten in growth rates as:

$$\sum_i D_i \sum_k (\varepsilon_{ik} - s_{ik}) dlnX_{ik} + \sum_i D_i \sum_j (\varepsilon_{ij} - s_{ij}) dlnM_{ij} - \sum_i D_i dlnF_i + \sum_i D_i dln\omega_i, \tag{9}$$

where D_i is the Domar weight, ε_{ik} and ε_{ij} are the elasticities of output with respect to primary and intermediate inputs, $s_{ik} = \frac{W_{ik}X_{ik}}{P_iQ_i}$ and $s_{ij} = \frac{P_jM_{ij}}{P_iQ_i}$ are the respective plant-specific revenue shares for both primary and intermediate inputs, and $dlnF_i$ and $dln\omega_i$ denoting the growth rates in fixed costs and technical efficiency, with the base given by Q_i.

If a value added production function exists (e.g., see Bruno (1978)), then we can express the decomposition as[1]

$$\sum_i \sum_k D_i^v(\varepsilon_{ik}^v - s_{ik}^v) dlnX_{ik} + \sum_i \sum_j D_i^v(\varepsilon_{ij}^v - s_{ij}^v) dlnM_{ij} - \sum_i D_i^v dlnF_i^v + \sum_i D_i^v dln\omega_i^v, \tag{10}$$

where $s_{ik}^v = \frac{W_{ik}X_{ik}}{VA_i}$ and $s_{ij}^v = \frac{P_j M_{ij}}{VA_i}$, and the elasticities are now those for the value added production function, which can be shown to equal the elasticities from the gross output production function divided by one minus the ratio of intermediate expenditures to revenues:

$$\varepsilon_{ij}^v = \frac{\varepsilon_{ij}}{1 - \sum_j s_{ij}}.$$

lnF^v denotes the growth rate in fixed costs divided by one minus the ratio of intermediate inputs expenditures to revenues. The value added technical efficiency shock is derived from the value added production function, which can be expressed as

$$ln\omega_i^v = ln(VA_i) - \sum_k \varepsilon_{ik}^v lnX_{ik} \tag{11}$$

with intercept β_0^v.[2] The relationship between the value added technical efficiency shock and the gross output production function technical efficiency shock is

$$ln\omega_i^v = \frac{ln\omega_i}{1 - \sum_j s_{ij}}. \tag{12}$$

We now discuss implementation of this index with discrete time data.

3 Discrete Time Approximation

The theory says that we can compute an approximation to APG directly from plant-level data without having to estimate production functions. However, up to this point all of the equations that we have considered have been

[1] A sufficient condition is that the intermediate inputs are separable in the gross output production function.

[2] If the elasticity of output with respect to each intermediate input is not equal to the intermediate's revenue share, then the estimated residual will include additional terms related to the intermediates.

written in continuous time, and the data we observe has been aggregated to discrete intervals. We use Tornqvist-Divisia approximations for all of our calculations. For example, for equation (6), the Tornqvist approximation is:

$$APG_{G,t} = \sum_i \overline{D}_{it}^v \Delta lnVA_{it} - \sum_i \sum_k \overline{c}_{ikt} \Delta lnX_{ikt} \quad (13)$$

where $\overline{D}_{it}^v$ is the average of plant i's value-added share weights from period t-1 to period t, Δ is the first difference operator from $t-1$ to t, $\overline{c}_{ikt}$ is the average across the two periods of plant i's expenditures for the kth primary input divided by aggregate value added.

Equation (7) can be estimated in discrete-time by:

$$\begin{aligned} APG_{G,t} &= \textstyle\sum_i \overline{D}_{it} \sum_k (\varepsilon_{ik} - \overline{s}_{ikt}) \Delta lnX_{ikt} + \sum_i \overline{D}_{it} \sum_j (\varepsilon_{ij} - \overline{s}_{ijt}) \Delta lnM_{ijt} \\ &\quad - \textstyle\sum_i \overline{D}_{it} \Delta lnF_{it} + \sum_i \overline{D}_{it} \Delta ln\omega_{it}, \end{aligned} \quad (14)$$

where again bars over variables denote two-period averages and Δ is the first-difference operator. Thus we need estimates of production function parameters and residuals to estimate the components of the decomposition. We estimate the production function parameters in logs and use them as estimates for ε_{ik} and ε_{ij}. For the growth rate in plant-level technical efficiency, we use the posited functional form for the production function to calculate the residuals, and then take the first difference. For example, if we assume a Cobb-Douglas production function, we would take first differences of an estimate of:

$$ln\omega_i = lnQ_i - (\sum_k \varepsilon_{ik} lnX_{ik} + \sum_j \varepsilon_{ij} lnM_{ij}). \quad (15)$$

We do not observe changes in fixed costs in our data directly, but we can estimate the aggregate fixed cost term as APG minus the aggregate reallocation and technical efficiency terms.

If intermediate inputs are separable in the production function then one can approximate the decomposition using a value added production function to construct estimates of the elasticities and changes in technical efficiency. In this case the decomposition is given as

$$\begin{aligned} APG_{G,t} &= \textstyle\sum_i \sum_k \overline{D^v}_{it} (\varepsilon_{ik}^v - \overline{s}_{ikt}^v) \Delta lnX_{ikt} + \sum_i \sum_j \overline{D^v}_{it} (\varepsilon_{ij}^v - \overline{s}_{ijt}^v) \Delta lnM_{ijt} \\ &\quad - \textstyle\sum_i \overline{D^v}_{it} \Delta lnF_{it}^v + \sum_i \overline{D^v}_{it} \Delta ln\omega_{it}^v, \end{aligned} \quad (16)$$

with the value added residual given as

$$ln\omega_i^v = lnVA_i - (\sum_k \varepsilon_{ik}^v lnX_{ik}) - \sum_j (\varepsilon_{ij}^v - s_{ijt}^v) lnM_{ijt} \tag{17}$$

In the case where the elasticity of output with respect to each intermediate input is equal to the ratio of expenditure on the input to total revenues, then the terms $\sum_j (\varepsilon_{ij}^v - s_{ijt}^v) lnM_{ijt}$ equal zero. Otherwise, the estimated value added residual will contain the reallocation terms associated with intermediate inputs.

4 Production Function and Technical Efficiency Estimation

One major advantage of the decomposition of APG in (9) is that many of the components are either directly observed or easy to estimate using standard plant-level data sets. Both Domar weights D_{it} and D_{it}^v are measurable as P_iQ_i and VA_i are observed for every plant-year. The shares in (9) are typically observed for all inputs but capital because plants report expenditures on their inputs. Finally, the plant-level data can also be used to estimate the parameters and technical efficiency terms for both gross output and value added production functions.

We estimate both the value added and the gross output specifications and their associated decompositions. We compare the estimated technical efficiency residuals across the two approaches - properly adjusted as in (12) - to see if differences between output elasticities and revenue shares for intermediate inputs are important in confounding technical efficiency in the value added case.

We observe every plant's nominal value of total shipments and we deflate nominal gross output by a 4-digit industry price index for shipments, denoted P_s for time period s, so our dependent variable in the gross output specifications is given as

$$ln\frac{P_{it}Q_{it}}{P_t} = lnQ_{it} + lnP_{it} - lnP_t. \tag{18}$$

Our definition of plant-level double deflated value added is given by

$$VA_{it}^{DD} = \frac{P_{it}Q_{it}}{P_t} - \frac{P_{iMt}M_{it}}{P_t^M} - \frac{P_{iEt}E_{it}}{P_t^E} \tag{19}$$

where we deflate expenditures on materials (M) and energy (E) using a 4-digit industry price indexes for materials (P_t^M) and energy (P_t^E). Our gross output production function specification includes three primary inputs: production worker labor (L^P), non-production worker labor (L^{NP}), and capital (K). For production workers we observe total number of hours at the plant and for non-production workers we observe number of people. We also have intermediate inputs, which includes the cost of parts and materials (M) and energy (E). For capital we use the real value of the total capital stock at the plant, constructed using the perpetual inventory method. The data appendix contains more detailed descriptions of our measures. Our value added specifications include just the three primary inputs as regressors.

We posit a Cobb-Douglas production function. We estimate production functions separately for each of our 459 4-digit SIC industries using Ordinary Least Squares, Levinsohn and Petrin (2003, LP), and Wooldridge (2009) variant of the LP estimator. While the different estimators have different strengths and weaknesses, our preferred estimator is the latter, which corrects for the simultaneous determination of inputs and technical efficiency, is robust to the Ackerberg, Caves, and Frazer (2008) criticism, and is one line of code in Stata.[3]

Given any estimator of production function coefficients our estimate of plant-level technical efficiency from the gross output specification is then

$$\begin{aligned} ln\widehat{\omega}_{it} = ln\tfrac{P_{it}Q_{it}}{P_{jt}} \quad & - \quad (\widehat{\epsilon}_{jP}\, lnL_{it}^P + \widehat{\epsilon}_{jNP}\, lnL_{it}^{NP} + \widehat{\epsilon}_{jK}\, lnK_{it} \\ & + \quad \widehat{\epsilon}_{jM}\, lnM_{it} + \widehat{\epsilon}_{jE}\, lnE_{it}) \end{aligned} \tag{20}$$

where $\widehat{\epsilon}_{j\cdot}$ denotes the estimated elasticities of output with respect to the inputs in 4-digit SIC industry j. Similarly, our estimate of technical efficiency

[3] We have publicly available programs for computing APG and its decomposition on Petrin's website. In each of these programs production function estimates are computed in six different ways. The code includes the one-line of Stata code that is Wooldridge-LP (it uses ivreg2.do).

for the value-added specification is given as

$$ln\widehat{\omega^v}_{it} = ln(VA_{it}) - \left(\widehat{\epsilon^v}_{jP}\, lnL^P_{it} + \widehat{\epsilon^v}_{jNP}\, lnL^{NP}_{it} + \widehat{\epsilon^v}_{jK}\, lnK_{it}\right) \tag{21}$$

where $\widehat{\epsilon^v}_{j\cdot}$ denotes the estimated elasticities of value added with respect to the inputs in 4-digit SIC industry j.

We now turn to the specifics of the Census data. Researchers interested in going directly to the results can skip to Section 6.

5 The Annual Survey of Manufacturers and Census Data

We use the U.S. Census Bureau's Annual Survey of Manufactures and Census of Manufactures, which provide a nationally representative sample for the entire U.S. manufacturing sector. These data include measures of the total (nominal) value of shipments, total expenditures on intermediate and primary inputs, and other input and output measures needed for our estimation.

The Census takes place in the years ending in 2 and 7, and includes approximately 200,000 manufacturing establishments that make up virtually all of aggregate value added.[4] The Annual Survey of Manufacturers (ASM) samples between 50,000 and 70,000 plants in U.S. manufacturing. With probability one the ASM samples all plants with more than 250 employees, all plants that are part of very large companies, and all plants in certain industries that are considered important to track. These plants account for approximately half of the sample. The other half includes plants that are sampled from the population with a probability related to the plant's value of shipments within each 5-digit product class.[5] The ASM sampling weight

[4]There are many other small plants from which data are not collected because they generate very little value added.

[5]The sampling probabilities for other plants are chosen to minimize the total cost of sampling, subject to a set of target variances. The targets are the sampling variances of the estimated change since the last Census in the value of shipments for each 4-digit SIC industry and each 5-digit product class. In 1994, Census changed the algorithm they

applied to these plants is then inversely proportional to the probability that the plant is sampled.

While the data we have is from the manufacturing sector and not the entire economy, P-L show that for any subset of plants in the economy we can decompose their contribution to aggregate value added. Entrants and exiters are included in APG in every year.[6]

Given the definition of plant-level value added (see equation 19) and the ASM sampling weights w_{it}, we estimate aggregate value added in manufacturing as

$$VA_t^{DD} = \sum_i w_{it} VA_{it}^{DD} \tag{22}$$

Our estimate of APG from $t-1$ to t is given by

$$\widehat{APG}_{G,t} = \sum_i \overline{D}_{it}^v \; \Delta ln VA_{it}^{DD} - \sum_i \sum_k \bar{c}_{ikt} \; \Delta ln X_{ikt} \tag{23}$$

where we define D_{it} and c_{ikt} in terms of the ASM sampling weights, with

$$D_{it}^v = \frac{w_{it} VA_{it}^{DD}}{VA_t^{DD}}, \tag{24}$$

$$\overline{D}_{it}^v = \frac{D_{it}^v + D_{i,t-1}^v}{2}, \tag{25}$$

$$c_{ikt} = \frac{w_{it} W_{ikt} X_{ikt}}{VA_t^{DD}}, \tag{26}$$

and

$$\bar{c}_{ikt} = \frac{c_{ikt} + c_{ik,t-1}}{2}. \tag{27}$$

k indexes three primary inputs: production worker labor (L^P), non-production worker labor (L^{NP}), and capital (K).

We observe the total wage bill both for production workers and non-production workers separately and can thus compute c_{ikt} for them directly.

used to select the sample, but the description above of the sampling weights still remains applicable.

[6]Decomposing changes in aggregate productivity growth from entry and exit is straightforward in levels. Decomposing growth rates with entry and exit cannot be done for the first year but can be done for every year after.

For capital expenditures we multiply the plant-level real stock of capital by the 2-digit industry level nominal rental price of capital, denoted P_t^K, and then weight:

$$c_{iKt} = \frac{w_{it} P_t^K K_{it}}{VA_t^{DD}}. \tag{28}$$

For production workers $\Delta ln L_t^P$ is the change in total hours from period $t-1$ to t. For non-production workers, $\Delta ln L_t^{NP}$ is the change in the number of laborers from period $t-1$ to t. For the change in capital $\Delta ln K_t$ we use the change in the real value of the total capital stock at the plant, constructed using the perpetual inventory method.

The decomposition is straightforward to calculate given the production function estimates. In the gross output case, the estimate for the change in aggregate technical efficiency is

$$\sum_i \overline{D}_{it} \Delta ln \widehat{\omega}_{it} \tag{29}$$

where

$$D_{it} = \frac{\sum_i w_{it} P_{it} Q_{it}}{VA_t^{DD}}. \tag{30}$$

As noted in PL, a lower bound on aggregate reallocation is given by

$$\widehat{APG}_{G,t} - \sum_i \overline{D}_{it} \Delta ln \widehat{\omega}_{it} \tag{31}$$

For any specific input X_{ijt} - either primary or intermediate - the reallocation term is

$$\sum_i (\overline{D}_{it} \widehat{\epsilon}_{j\cdot} - \overline{c}_{ijt}) \Delta ln X_{ijt}. \tag{32}$$

The decomposition for reallocation for value added follows the same approach.The change in aggregate technical efficiency is given by

$$\sum_i \overline{D}_{it}^v \Delta ln \widehat{\omega^v}_{it}, \tag{33}$$

and for any primary input X_{ijt} the reallocation term is given by

$$\sum_i (\overline{D}_{it}^v \widehat{\epsilon^v}_{j\cdot} - \overline{c}_{ijt}) \, \Delta ln X_{ijt}. \tag{34}$$

6 Estimates of APG using the ASM

In this section we present estimates of APG from the ASM data and compare these results to estimates of aggregate productivity growth using other indexes. In the Appendix we compare our estimates of value added to several alternative estimators and find that the results are similar (see Table A1).

6.1 APG and Its Decomposition Using Gross Output Production Functions

Table 1 shows estimated APG and its decomposition (using (23)) for the entire U.S. manufacturing sector. This includes changes in aggregate value-added and changes in the aggregate costs of capital, production-worker labor, and non-production-worker labor. While aggregate value-added in manufacturing grew by an average of 2.3% per year, aggregate costs of capital and non-production labor grew very little over this period.[7] The growth rate of aggregate value-added was also much more volatile than the growth rates of aggregate primary input costs.

The final column of table 1 shows our estimates of aggregate productivity growth. Since the growth rates of aggregate primary input costs are close to zero in most years, APG basically follows the growth rate of aggregate value-added with a slightly smaller variance. The mean is approximately the same (2.2% for APG) and the contemporaneous correlation between aggregate value-added growth and APG is 0.98.

Next we decompose APG into productivity growth due to within-plant technical efficiency growth and growth due to the reallocation and fixed cost terms. We estimate the production functions using OLS, LP, and the Wooldridge (2009) modification of LP. Table 2 shows the results from the Wooldridge estimator.[8] For comparison, column 1 of Table 2 is the growth

[7]The biggest outlier is 1982, when our measure of aggregate production labor costs declined by 3.6%.

[8]Results for the LP and OLS estimators are presented in tables A2a and A2b respectively in the Appendix.

rate of aggregate real value-added and column 2 is APG from column 5 of Table 1. Column 3 of Table 2 shows the contribution of technical efficiency growth to APG. Total reallocation (column 4) is the sum of the reallocation "gap" terms for primary and intermediate inputs in equation (14).

Technical efficiency and reallocation make important contributions to aggregate productivity growth, both in terms of the average growth rate and the volatility of aggregate productivity growth. Reallocation makes a larger contribution on average, whereas most of the volatility in aggregate productivity growth is coming from aggregate technical efficiency growth. The contribution of total reallocation is positive in all but 3 years, which one would expect from a well-functioning market economy where resources on average move from lower-value to higher-value activities.

The final column of Table 2 shows the difference between APG and the sum of the technical efficiency and total reallocation terms. This residual term includes any fixed costs which are not already captured by the technical efficiency term. In almost all years, the fixed costs residual term is small relative to the total reallocation term in column (1), indicating that the reallocation "gap" terms explain most of the growth of aggregate productivity that is not due to technical efficiency growth.

There are multiple sources of variation in these gap terms. Anything that drives a wedge between the marginal product and the marginal cost of an input - like markups, taxes/subsidies, or adjustment costs - lead to a role for APG growth from the reallocation of inputs. A particular input for a plant can contribute positively to the reallocation term because of a positive gap and a positive growth rate of that input or because of a negative gap and a decline in the use of that input.

In Table 3a we present our decompositions of aggregate productivity growth due to reallocation into the contributions of the "gap" terms associated with each factor of production using Wooldridge-LP. The largest share of the annual variation in aggregate productivity growth due to reallocation is coming from variation in the intermediate materials gap term, although production worker labor reallocation is important in some years. We are investigating the large fluctuations in the contribution of reallocation of intermediate materials, which may be due to large fluctuations in the growth rates of intermediate materials and relatively constant gaps between the output elasticities and input cost shares. Capital's contribution is relatively stable and almost always positive.The growth rates of the individual gap terms are also less volatile than the aggregate technical efficiency terms in Tables 3a. These results are robust across the LP and OLS estimators (see Tables A3a/A3c).

In Table 3b we show the correlations of the individual reallocation gap terms with total reallocation and with each other. The materials reallocation term is strongly correlated with total reallocation, and the energy and production worker reallocation terms are also positively correlated with total reallocation. Non-production worker reallocation is negatively correlated with total reallocation and with the reallocation of all the other inputs except energy, and capital reallocation is essentially uncorrelated with reallocation of all of the other inputs except energy.[9]

6.2 Value-added Results

The results in Tables 2 and 3 are constructed from gross-output production functions. For many settings, value-added production functions are more convenient to estimate, but they require stronger conditions on the production technology (e.g. separability of intermediate inputs). Overall we find similar qualitative results between the value-added and the gross output production functions, but only *after* we correct the estimated value-added technical efficiency residual by removing the intermediate input reallocation term that exists if elasticities of intermediate inputs differ from their revenue shares (see equation (16)).

Tables 4 and 5a-b present the results of the decomposition of APG into aggregate technical efficiency and total reallocation, where the value-added production functions are estimated using Wooldridge-LP. Comparing these results to the gross-output results in Table 2, the most striking difference is that for the value-added specification the total reallocation term (column

[9] For OLS or LP see Tables A3b/A3d.

3) is even more stable: its standard deviation is only 0.7 (compared to 1.7 in the gross-output specification), and it is negative in only one year. As in the gross-output case, the total reallocation term makes a significant contribution to aggregate productivity growth–about 0.9 percentage points per year. In the value-added specification, estimated aggregate technical efficiency (column 2) is much more volatile than reallocation–the standard deviation is 3.5–and it contributes about 1.3 percentage points per year to APG over the period 1976-1996.

The differences between the results in columns 2 and 3 of table 4 and columns 3 and 4 of table 2 are principally explained by the intermediate reallocation term confounding technical efficiency. In table 3a, these intermediate "gap" terms are important in several years.[10] Column 4 of table 4 shows the results when we subtract the intermediate reallocation terms from the gross output case (columns 4 and 5 in table 3) from the technical efficiency growth term in the value-added case (column 2 of table 4). In most years, this "corrected" value-added technical efficiency growth is close to gross output technical efficiency growth, and the mean and standard deviation of this corrected term (0.4% and 2.8%, respectively) are very close to the mean and standard deviation of gross-output technical efficiency (0.2% and 2.7%, respectively). Our results suggest that business cycle models that assume the existence of a valued-added production function in an economy with perfect competition and no frictions or distortions attribute too much growth to the direct effect of technology shocks.

6.3 Industry-level APG Decompositions

One of the beauties of the APG decomposition is that it allows us to investigate how much individual industries contribute to aggregate productivity growth. To keep the volume of results manageable, we computed aggregate productivity growth decompositions at the 2-digit SIC industry level. To compute the industry-level decompositions, we took the plant-level technical efficiency and reallocation terms and weighted them by the plant's Domar

[10] The same result holds for either the LP or OLS estimator.

weight *within that 2-digit industry.* In other words, for these industry-level decompositions, the Domar weight of plant i is:

$$D_i^{SIC2} = \frac{P_i Q_i}{\sum_{i \in SIC2} VA_i} \tag{35}$$

where the denominator of the Domar weight is the aggregate value-added of that 2-digit SIC industry. When we weight the resulting industry-level technical efficiency and reallocation terms by each 2-digit industry's share of manufacturing valued-added, the industry-level terms sum up to aggregate productivity growth for the entire manufacturing sector.

Table 6 presents summaries of the industry-level decompositions for each 2-digit SIC manufacturing industry for the gross-output specification estimated with the Wooldridge-LP estimator.[11] Columns 1 and 2 show the time series mean and standard deviations for technical efficiency growth. Columns 3 and 4 show the means and standard deviations for the sums of the reallocation "gap" terms. For most industries, the patterns we found for the entire manufacturing sector also hold at the 2-digit industry level: the average contribution of reallocation is greater than the time-series average of technical efficiency growth, and technical efficiency growth is significantly more volatile than growth from reallocation. These results are robust across gross output and value added production function specifications and the LP and OLS estimators (see Tables A6a-A7c in the Appendix).

Table 6 also shows significant variation across industries in the relative contributions of reallocation and technical efficiency growth. Column 5 shows each 2-digit industry's average share of manufacturing value-added over the period 1976-1996. The average contribution of reallocation at the 2-digit industry level varies from -2.3 percentage points (for food & tobacco products) to 5.1 percentage points (electronic equipment), while the average

[11] Only for the industry-level decompositions do we combined tobacco products industries (2-digit SIC=21) with food manufacturing industries (20) in order to comply with Census Bureau disclosure avoidance rules. Tobacco product manufacturing in the U.S. is highly concentrated. Therefore, when we aggregated, we combined tobacco products industries with food manufacturing industries (SIC2='20'). We estimated all industry production functions at the 4-digit SIC industry level.

contribution of technical efficiency growth at the 2-digit industry level varies from -2.7 percentage points (wood products) to 4.4 percentage points (food and tobacco). Some industries have above-average growth rates, but are a relatively small share of aggregate value-added (rubber & plastics), whereas others are large, but are not growing very fast (e.g., transportation equipment). The average industry shares range from 0.4% (leather products) to 12.2% (food and tobacco products).

Column 6 of Table 6 shows the proportion of years in which the 2-digit-industry-level total reallocation terms were positive. Just as we saw at the manufacturing sector level, we find that for most industries reallocation contributes positively to aggregate productivity growth in the vast majority of years.

Table 7 presents time-series means and standard deviations of the industry-level reallocation terms for each input for each 2-digit industry. Again, there is significant industry-level variation in the contributions of different inputs. For example, the within-industry average contribution of materials reallocation ranges from -1.0 percentage points (for petroleum and coal products) to 2.0 percentage points (industrial machinery). The within-industry standard deviation of materials reallocation ranges from 0.6 (paper products) to 4.2 (food and tobacco products).

6.4 Comparing APG to Productivity Measures Based Only on Technical Efficiency Change

While we are the first to apply the APG decomposition to U.S. data, many studies have used the ASM and the Census to decompose aggregate productivity growth using some variant of the BHC productivity index, like those found in Foster, Haltiwanger, and Krizan (2001) and Olley and Pakes (1996). These indices are defined completely in terms of the plant-level technical efficiency residual. In continuous time the BHC index is given as:

$$BHC \equiv d\sum_i (s_i \, ln\omega_i) = \sum_i s_i \, dln\omega_i + \sum_i ln\omega_i ds_i, \tag{36}$$

where s_i is either the gross-output share or the labor share for plant i.

The BHC measure decomposes into the two right-hand-side terms. The first term is referred to as the technical efficiency or "within" term and the second term is known as the reallocation or "between" term. An empirical regularity from many plant-level panels is that the reallocation term from BHC takes on negative values that are frequently large relative to the technical efficiency term in the aggregate (see Petrin and Levinsohn, 2010 and Kwon, Narita, and Narita (2009)). In a market economy populated by profit-maximizing firms it is difficult to see why reallocation of primary inputs should have such large negative effects in the aggregate on APG, something we do not find for our definition of reallocation.

BHC growth measured with discrete time data and the Tornquist-Divisia approximation is then

$$BHC_t = \sum_i s_{it} ln\omega_{it} - \sum_i s_{i,t-1} ln\omega_{i,t-1} \tag{37}$$

with decomposition

$$BHC_t = \sum_i \frac{(s_{it} + s_{i,t-1})}{2} \Delta ln\omega_{it} + \sum_i \frac{(ln\omega_{it} + ln\omega_{i,t-1})}{2} * \Delta s_{it}. \tag{38}$$

On the technical efficiency term, the BHC-type indexes use either labor share or gross output share as the weight, where APG weights by the Domar weight. The only case in which the Domar weight will equal the gross output share is when there are no intermediate input deliveries in the economy. Otherwise the difference between the two is increasing in the fraction of gross output that goes to intermediate input use. For example, if every plant has a ratio of materials expenditures to revenues of 50% (typical for manufacturing), then the BHC technical efficiency growth is exactly half of APG technical efficiency growth.

Empirically we want to focus on the differences in reallocation between BHC and APG, so we abstract from differences in technical efficiency by using the Domar weight for both BHC and APG technical efficiency growth in Table 8. The volatility of growth due to reallocation is enormous for BHC: the standard deviation of the annual rate is as high as 7.8 percentage points – more than 4 times the volatility of the APG measure of reallocation. In many years, the contribution of BHC-measured reallocation is both large (in absolute value) and negative, sometimes indicating a decline of more than 20% in a single year. These results are robust to OLS and LP (see Tables A8a and A8b), and suggest the way one defines aggregate productivity growth can have a substantial impact on how one interprets the roles of technical efficiency and reallocation in any economy.

7 Conclusions and Suggestions for Further Research

We provide the first application of the Petrin and Levinsohn (2010) aggregate productivity growth statistic and decomposition to U.S. data. We adopt this definition because it insists that micro-level changes add up to changes in aggregate final demand holding primary inputs constant. We decompose aggregate productivity growth into the contributions of technical efficiency and reallocation. Over the period 1976-1996, in the U.S. manufacturing sector we find that both contributions are important. On average reallocation was responsible for about 1.7 to 2.1 percentage points per year, and it was positive in all but 3 years. Technical efficiency growth was responsible for only 0.2 to 0.6 percentage points per year, but it was more volatile: our estimates of the standard deviation of the annual growth rate range from 2.6 to 3.0 percentage points, compared to 1.1 to 1.7 percentage points for reallocation. The results are robust to several different production function estimators.

Our results have implications for both the theoretical literature on growth and alternative plant-level indexes of aggregate productivity growth like the BHC index and its derivatives. We can sort between the theoretical models as they have implications for whether/how growth takes place from plant-level technical efficiency changes and related reallocations of resources. For example, Melitz (2003) and other models of micro-level growth rule out technical efficiency change and attribute all growth to reallocation towards the more technically efficient firms. Our results suggest that while reallocation does play an important role in growth, it only accounts for half of growth, and a single-index of reallocation at the plant-level - and one only related to technical efficiency - do a poor job of characterizing U.S. manufacturing growth over our sample period. This finding also suggests that plant-level aggregate productivity growth indices based only on technical efficiency miss a large source of growth, and mischaracterize reallocation growth by looking at only technical efficiency and not considering each input gap individually.

Appendix A: Data

We use the Census Bureau's confidential Census of Manufactures (CMF, conducted in years ending in 2 and 7), the Annual Survey of Manufactures (ASM), and the Bureau's Longitudinal Business Database (LBD). In Census years we use only the plants receiving the ASM questionnaire, since that survey instrument askes more detailed questions about costs than the non-ASM questionnaire sent to other plants in the Census years.[12] For deflators and depreciation rates we use the dataset available on John Haltiwanger's web site: http://www.econ.umd.edu/ haltiwan/capital/CRIWNBER/external.sas7bdat (last accessed on October 1, 2008).

Our unit of analysis is the plant. Consistent with most researchers who use this microdata, we drop administrative records plants from the sample, because most of the cost data for these plants is imputed.

Industry coding. We use SIC industry codes at the 4-digit level. The SIC system of coding industries has changed over time, most notably in 1987 and in 1997. In the Census years, the plants have been recoded using the 1987 SIC system based on the 7-digit products that the plants were producing in each Census year. We use the 1987 SIC coding system and the Census years to create consistent 4-digit SIC industries across time using the microdata. In cases where we could not recode industries this way, we use a concordance from the 1977/1982 SIC system to recode the plants into the 1987 SIC system. Our coding scheme gives us 459 industries.

Table A1 shows the annual growth rates of real GDP and four different measures of the growth rates of aggregate real value-added in manufacturing: from the National Income and Product Accounts (NIPA), from the NBER-CES manufacturing productivity database, and two different measures from the plant-level ASM data.[13] To calculate the estimates in column (4), we first used equation (22) to computed aggregate real value-added using all plants in the ASM for which we could compute real value-added, and then

[12] The LBD is described in Jarmin and Miranda (2002).

[13] Unfortunately real value-added for manufacturing is only available on the BEA website starting in 1987.

we computed the growth rates of these aggregates. For column (5), we selected only plants which are continuers from one year to the next and for which we could compute plant-level estimates of productivity. Then we computed the growth rate of aggregate real value-added as a Tornqvist index, as in the first term in equation (23).

The average annual growth rate (AAGR) of real GDP over this period was about 2.5%, while our estimates of the AAGR of manufacturing value-added range from 2.3% for the Tornqvist index based on continuing ASM plants to 3.6% in the NBER-CES database. The growth rate of manufacturing valued-added was more volatile than that of GDP: our estimates of its standard deviation range from 4.6% for the Tornqvist index of continuing ASM plants to 6.0% for the ASM measure that uses all plants. This is compared to a standard deviation of only 2.4% for the growth rate of real GDP. The correlation between the growth rate of manufacturing valued-added for continuers and the GDP growth rate during this period is 0.78.

The numbers from the plant-level ASM do not exactly match the aggregate real value-added growth rates from the NIPA both because the samples are different, and because the value-added measures used by the Census Bureau and the BEA are somewhat different. However, the numbers are quite similar in most years.

The differences between columns (4) and (5) illustrate the impact of entry and exit in the ASM. At the beginning of each ASM panel, a little less than half of the plants exit the panel and are replaced. If we exclude the first year of each ASM panel–years ending in 4 or 9–then in most years the growth rate of aggregate real value-added based on all ASM plants is close to the growth rate computed only for continuing ASM plants.[14]

Despite the differences in the samples and value-added measures, our estimates from the ASM do generally track the growth rates of manufacturing value-added from other sources. In particular we can clearly see the contractions in 1980, 1982, and 1990/1991, and the expansions in the 1980s and 1990s, and the standard deviation of our estimates of the growth rate of aggregate value added (column 5) is about the same as the standard deviation

[14]We discuss entry and exit in greater detail in Appendix C.

of the growth rates of aggregate value from the NBER-CES productivity database (4.7 versus 4.6 percentage points, respectively). The correlation between our measure of aggregate value-added from continuing ASM plants and manufacturing aggregate real value-added from the NIPA (for the years for which we have real value-added from the NIPA) is 0.97.

Output. The nominal dollar total value of shipments, TVS, is observed in the ASM/CMF. Note that the surveys ask multi-plant firms to report the operations of each plant as a separate economic unit. Thus the shipments from one plant to another plant in the same firm are supposed to be included in the total value of shipments of the shipping plant, and they are supposed to be included in the total cost of materials of the receiving plant. We also observe inventories for finished goods and work-in-progress at the beginning and end of the year (FIB, FIE, WIB, and WIE). Our measure of real gross output is (TVS+(FIE-FIB)+(WIE-WIB))/PISHIP, where PISHIP is the 4-digit SIC industry-level shipments deflator from the NBER/CES Productivity database.

Value-added. Nominal value-added is nominal total value of output minus the nominal value of intermediate inputs (VM). Our measure of double-deflated real value-added is the real total output minus the real total cost of intermediates.

Production-worker hours. Thousands of total annual plant hours worked by production workers at a plant are measured directly in the ASM and CMF. For **production worker costs** in the numerator of equation (26), we use total annual production worker wages at the plant. For **non-production worker costs** we use total salaries and wages less total production worker wages at the plant.

Intermediate inputs. The total cost of intermediate inputs (VM) is the sum of the cost of materials and parts (CP), the cost of fuels (CF), the cost of purchased electricity (EE), the cost of resales (CR), and the cost of contract work (CW), all measured in nominal dollars. The real total cost of intermediates is VM/PIMAT, where PIMAT is the 4-digit industry-level deflator for materials from NBER-CES productivity database. For the gross-output production functions, we also break out intermediate inputs into the real **cost of materials**, (CP+CR+CW)/PIMAT, and the real **cost of energy**, (CF+EE)/PIEN, where PIEN is the energy deflator from the NBER-CES productivity database.

Capital. We use the perpetual inventory method to construct a measure of total real capital stock for each plant using the book value of the plant's assets (appropriately deflated), the plant's real capital expenditures (including rentals of equipment and structures), and industry-specific capital depreciation rates. For each plant we construct separate stocks for machinery/equipment and building/structures, and then we sum them to get the total capital stock for the plant.

The initial capital stock is the book value of assets at the beginning of the year deflated to thousands of 1987 dollars using industry-level asset deflators. For example, for equipment, the real initial capital stock is computed as: initial stock = (initial nominal book value)*(nkceq/gkheq)*(piinve87/piinve96), where nkceq = the real value of net equipment capital stock in millions of 1996 dollars for a given year for an entire 2-digit SIC industry; gkheq = the book value of gross equipment capital stocks (in millions of historical dollars) for a given year for an entire 2-digit SIC industry; piinve96 = the 3-digit industry equipment investment deflator (PIINVE) for 1996, where 1987 is the base year; piinve87= 1. We follow an analogous procedure for buildings or structures. After the initial year, the plant's capital stock is the undepreciated stock from the previous year plus total real capital expenditures from the previous year.

To construct the capital cost shares in equation (26), we need an estimate of the user cost of capital. We use equipment ("machinery") capital rental prices (at the 2-digit SIC industry level) and the structures ("buildings") capital rental prices constructed from BLS data.

In later years we have to deal with several missing data issues to construct our capital stocks measures. For plants that enter the ASM after 1986 and survive until a census year, we construct initial capital stocks using backwards and forwards perpetual inventory, starting in the first census year that the plant is observed. Furthermore, after 1992, the ASM only collected the total book value of assets, rather than separate book values for machinery and buildings. To impute the book value machinery assets in 1997, we accumulate the plant's expenditures on machinery over all the years of the plant's existence prior to 1997 and multiply the total assets variable by the ratio of cumulated machinery investment to total investment over the same period. We follow the analogous procedure for investment in buildings.

References

Ackerberg, D., K. Caves, and G. Frazer (2008): "Structural Identification of Production Functions," Working Paper.

Baily, M., C. Hulten, and D. Campbell (1992): "Productivity Dynamics in Manufacturing Plants," *Brookings Papers on Economic Activity.*

Basu, S., and J. Fernald (2002): "Aggregate Productivity and Aggregate Technology," *European Economic Review*, 46, 963–991.

Bruno, M. (1978): "Duality, Intermediate Inputs and Value-Added," in *Production Economics: A Dual Approach to Theory and Applications*, ed. by M. Fuss, and D. McFadden. North-Holland.

Foster, L., J. Haltiwanger, and C. Krizan (2001): *New Developments in Productivity Analysis*chap. Aggregate Productivity Growth: Lessons from Microeconomic Evidence, pp. 303–372. University of Chicago Press.

Hall, R. (1988): "The Relation Between Price and Marginal Cost in U.S. Industry," *Journal of Political Economy*, 96, 921–947.

——— (1990): "Invariance Properties of Solow's Productivity Residual," in *Growth/Productivity/Employment: Essays to Celebrate Bob Solow's Birthday*, ed. by P. Diamon. MIT Press.

Hsieh, C.-T., and P. J. Klenow (2009): "Misallocation and Manufacturing TFP in China and India," *Quarterly Journal of Economics*, 74(5), 1403–1448.

Hulten, C. (1978): "Growth Accounting with Intermediate Inputs," *The Review of Economic Studies*, 45(3), 511–518.

Jarmin, R., and J. Miranda (2002): "The Longitudinal Business Database," Census Bureau Center for Economic Studies Discussion Paper CES-02-17.

Kwon, H. U., F. Narita, and M. Narita (2009): "New Evidence on Japan's Productivity Growth in the 1990s," Working Paper.

Levinsohn, and Petrin (2003): "Estimating Production Functions Using Inputs to Control for Unobservables," *Review of Economic Studies*.

Melitz, M. (2003): "The Impact of Trade on Intra-Industry Reallocations and Aggregate Industry Productivity," *Econometrica*.

Olley, S., and A. Pakes (1996): "The Dynamics of Productivity in the Telecommunications Equipment Industry," *Econometrica*, 64(6), 1263–1298.

Petrin, A., and J. Levinsohn (2010): "Measuring Aggregate Productivity Growth Using Plant-Level Data," Working Paper.

Solow, R. M. (1957): "Technical Change and the Aggregate Production Function," *Review of Economics and Statistics*, 39(3), 312–320.

Wooldridge, J. (2009): "On Estimating Firm-Level Production Functions Using Proxy Variables to Control for Unobservables," Economic Letters.

Table 1: Percentage Growth Rates of Value-Added, Primary Input Costs and Aggregate Productivity in U.S. Manufacturing, 1977–1996.

	(1)	(2)	(3)	(4)	(5)
Year	Value Added	Production labor costs	Non-production labor costs	Capital costs	Aggregate Productivity (APG)
1977	6.2	1.1	0.4	0.3	4.3
1978	5.5	0.9	0.5	0.4	3.6
1979	6.4	0.0	0.5	0.4	5.3
1980	-6.2	-2.1	0.6	0.4	-5.1
1981	2.7	-0.5	-0.0	0.5	2.7
1982	-8.0	-3.6	-0.4	0.5	-4.5
1983	5.9	0.0	-0.4	0.3	5.9
1984	8.6	1.4	0.2	0.1	6.8
1985	0.5	-0.5	0.3	0.4	0.3
1986	-0.3	-0.6	0.1	0.4	-0.3
1987	6.7	0.0	-0.3	0.3	6.7
1988	5.1	0.4	0.0	0.3	4.4
1989	-0.7	-0.2	0.0	0.3	-0.9
1990	-3.1	-0.7	-0.2	0.4	-2.5
1991	-2.4	-0.8	-0.1	0.4	-2.0
1992	3.4	-0.0	-0.5	0.2	3.7
1993	1.9	0.0	-0.3	0.3	1.9
1994	6.9	0.4	-0.2	0.2	6.5
1995	4.7	0.0	0.0	0.3	4.2
1996	2.9	0.0	-0.1	0.5	2.5
Mean	2.3	-0.2	0.0	0.3	2.2
s.d.	4.6	1.1	0.3	0.1	3.7

Note: (1) - (2) - (3) - (4)= (5)

Table 2: Aggregate Productivity Growth Decomposition
Technical Efficiency and Reallocation. U.S. Manufacturing 1977–1996

	Percentage Growth Rates of ...				
			(2)=(3)+(4)-(5)		
	(1)	(2)	(3)	(4)	(5)
Year	Value Added	Aggregate Productivity (APG)	Technical Efficiency (TE)	Reallocation (RE)	Fixed Costs Residual Error
1977	6.2	4.3	-0.5	4.6	-0.3
1978	5.5	3.6	1.0	2.4	-0.2
1979	6.4	5.4	3.1	1.0	-1.3
1980	-6.2	-5.1	-3.9	-0.3	0.9
1981	2.7	2.8	-0.1	1.4	-1.4
1982	-8.0	-4.5	-2.9	-1.4	0.2
1983	5.9	5.9	4.2	1.6	-0.1
1984	8.6	6.8	1.9	4.9	-0.1
1985	0.5	0.3	-3.5	3.5	-0.4
1986	-0.3	-0.2	-4.3	3.9	-0.2
1987	6.7	6.7	3.1	2.9	-0.7
1988	5.1	4.4	2.1	2.4	0.0
1989	-0.7	-0.9	-2.3	1.7	0.2
1990	-3.1	-2.5	-0.4	-1.1	0.9
1991	-2.5	-2.0	-2.7	1.9	1.2
1992	3.4	3.7	3.0	1.2	0.5
1993	1.9	1.9	0.1	2.6	0.7
1994	6.9	6.5	3.9	3.0	0.4
1995	4.7	4.2	2.2	2.4	0.4
1996	2.9	2.5	0.6	3.2	1.3
Mean	2.3	2.2	0.2	2.1	0.1
s.d.	4.6	3.7	2.7	1.7	0.7

Gross Output Production Functions estimated by Wooldridge (2009) modification of Levinsohn and Petrin (2003) estimator.

Table 3a: Decomposition of Reallocation Term (equation 9): U.S. Manufacturing, 1977–1996

	Percentage Growth Rates of ...					
	(1)	(2)	(3)	(4)	(5)	(6)
		Reallocation "Gap" terms				
Year	Reallocation (RE)	Production workers	Non-Production workers	Materials	Energy	Capital
1977	4.6	0.8	0.1	2.2	0.6	0.9
1978	2.4	0.5	0.1	1.5	0.0	0.2
1979	1.0	0.2	0.1	0.5	-0.4	0.6
1980	-0.3	-0.5	0.1	-0.5	-0.4	1.1
1981	1.4	0.0	0.0	-0.1	0.8	0.7
1982	-1.4	-0.6	0.2	-2.0	1.4	-0.4
1983	1.6	0.4	0.1	0.2	1.2	-0.3
1984	4.9	0.7	-0.1	3.4	0.7	0.1
1985	3.5	0.3	-0.1	0.9	1.1	1.3
1986	3.9	0.3	0.1	0.7	1.1	1.7
1987	2.9	0.2	0.2	1.0	0.3	1.2
1988	2.4	0.5	0.1	1.2	0.6	0.0
1989	1.7	0.7	0.0	0.4	0.1	0.5
1990	-1.1	0.8	0.1	-1.8	-1.7	1.5
1991	1.9	0.6	0.1	-0.7	-0.1	2.0
1992	1.2	0.4	0.1	0.9	-0.6	0.5
1993	2.6	0.5	0.1	0.2	0.4	1.3
1994	3.0	0.1	0.0	1.9	0.2	0.8
1995	2.4	0.1	0.1	1.3	-0.3	1.3
1996	3.2	-0.0	0.0	2.1	-0.1	1.2
Mean	2.1	0.3	0.1	0.7	0.2	0.8
s.d.	1.7	0.4	0.1	1.3	0.7	0.7

Note: (1) = (2) + (3) + (4) + (5) + (6)
(numbers may not add up exactly due to rounding.)

Gross Output Production Functions estimated by Wooldridge (2009) modification of Levinsohn and Petrin (2003) estimator.

Table 3b: Correlations of Reallocation Terms

	Reallocation (RE)	Production workers	Non-Production workers	Materials	Energy	Capital
Reallocation	1.00					
Production Workers	0.35	1.00				
Non-production Workers	-0.30	-0.29	1.00			
Materials	0.81	0.30	-0.48	1.00		
Energy	0.48	-0.20	0.09	0.17	1.00	
Capital	0.03	0.15	-0.03	-0.09	-0.39	1.00

Table 4: Aggregate Productivity Growth Decomposition
Technical Efficiency and Reallocation. U.S. Manufacturing 1977–1996
(Value-Added Production Functions)

	Percentage Growth Rates of ...			
	APG=TE+RE			
	(1)	(2)	(3)	(4)
	Aggregate	Technical		TE -
	Productivity	Efficiency	Reallocation	Intermediates
Year	(APG)	(TE)	(RE)	Reallocation
1977	4.3	3.0	1.3	0.2
1978	3.6	1.9	1.7	0.4
1979	5.4	3.4	1.9	3.3
1980	-5.1	-6.4	1.3	-5.5
1981	2.8	1.3	1.5	0.6
1982	-4.5	-4.7	0.2	-4.1
1983	5.9	5.7	0.2	4.3
1984	6.8	5.5	1.3	1.4
1985	0.4	-1.0	1.4	-2.9
1986	-0.3	-1.6	1.4	-3.4
1987	6.7	5.5	1.2	4.2
1988	4.4	3.3	1.1	1.6
1989	-0.9	-1.0	0.1	-1.4
1990	-2.5	-1.5	-1.0	2.0
1991	-2.0	-2.3	0.3	-1.5
1992	3.7	3.3	0.4	3.1
1993	1.9	1.5	0.4	0.9
1994	6.5	5.8	0.7	3.6
1995	4.2	3.6	0.6	2.6
1996	2.5	1.2	1.3	-0.7
Mean	2.2	1.3	0.9	0.4
s.d.	3.7	3.5	0.7	2.8

Value-added Production Functions estimated by Wooldridge (2009) modification of Levinsohn and Petrin (2003) estimator.

Table 5a: Decomposition of Reallocation Term (equation 10): U.S. Manufacturing, 1977–1996 (Value-Added Production Functions)

	Percentage Growth Rates of ...			
	(1)	(2)	(3)	(4)
Year	Reallocation (RE)	Production worker "gap" term	Non-Production worker "gap" term	Capital "gap" term
1977	1.3	0.3	0.3	0.7
1978	1.7	0.7	0.2	0.9
1979	1.9	0.3	0.6	1.0
1980	1.3	-0.2	0.2	1.3
1981	1.5	0.2	0.1	1.2
1982	0.2	-1.1	0.4	0.9
1983	0.2	-0.7	0.1	0.8
1984	1.3	0.4	0.1	0.8
1985	1.4	0.0	0.0	1.3
1986	1.4	0.0	0.1	1.3
1987	1.2	0.2	0.0	1.0
1988	1.1	0.4	0.0	0.6
1989	0.1	-0.1	-0.4	0.7
1990	-1.0	-1.5	-0.4	1.0
1991	0.3	-0.6	0.1	0.8
1992	0.4	0.0	-0.2	0.6
1993	0.4	-0.4	-0.1	0.9
1994	0.7	0.1	0.0	0.7
1995	0.6	-0.1	-0.2	0.9
1996	1.3	0.4	0.0	0.9
Mean	0.9	-0.1	0.0	0.9
s.d.	0.7	0.5	0.2	0.2

Value-added Production functions estimated by Wooldridge (2009), modification of Levinsohn and Petrin (2003) estimator.

Table 5b: Correlations of Reallocation Terms

	Reallocation (RE)	Production workers	Non-Production workers	Capital
Reallocation	1.00			
Production Workers	0.86	1.00		
Non-production Workers	0.66	0.32	1.00	
Capital	0.34	-0.06	0.23	1.00

Table 6: Summaries of Aggregate Productivity Growth Decompositions By 2-digit SIC Manufacturing Industry, 1977–1996

SIC2	Industry	(1) Technical Efficiency Growth (%) (mean)	(2) (s.d.)	(3) Reallocation (% Growth) (mean)	(4) (s.d.)	(5) Value-Added Share (%) (mean)	(6) Positive Reallocation (proportion of years)
20 & 21	Food & Tobacco Products	4.4	7.7	-2.3	6.4	12.2	0.35
22	Textiles	1.1	5.1	1.6	1.6	2.3	0.80
23	Apparel	-0.9	3.0	2.2	1.6	2.3	0.90
24	Wood Products	-2.7	4.5	2.2	2.9	2.0	0.80
25	Furniture	-1.7	3.4	2.6	2.7	1.5	0.80
26	Paper Products	0.7	3.1	0.6	1.4	4.5	0.75
27	Printing & Publishing	-1.6	2.2	1.7	1.9	5.1	0.75
28	Chemicals	-1.4	4.5	2.8	2.0	11.0	0.90
29	Petroleum & Coal Products	2.7	16.1	0.2	5.1	1.8	0.55
30	Rubber & Plastics	0.0	4.0	2.7	2.4	3.7	0.90
31	Leather Products	-0.7	4.1	0.6	4.0	0.4	0.70
32	Stone, Clay, & Glass	0.4	3.6	1.0	3.0	2.7	0.75
33	Primary Metals	0.1	7.2	1.4	0.9	5.1	0.95
34	Fabricated Metal Products	-1.1	4.3	1.9	1.4	6.6	0.90
35	Industrial Machinery	0.5	3.6	4.5	4.2	10.7	0.90
36	Electronic Equipment	2.3	6.4	5.1	2.9	8.7	1.00
37	Transportation Equipment	-1.0	5.1	1.7	3.6	11.9	0.70
38	Instruments	-1.8	2.8	4.2	1.9	6.1	1.00
39	Miscellaneous	-2.1	4.6	3.4	1.8	1.4	1.00

Gross Output Production Functions estimated by Wooldridge (2009) modification of Levinsohn and Petrin (2003) estimator.

Table 7: Summaries of Reallocation "Gap" Terms
Percentage Growth Rates
By 2-digit SIC Manufacturing Industry, 1977–1996

	(1)		(2)		(3)		(4)		(5)	
	Production workers		Non-Production workers		Materials		Energy		Capital	
Industry	(mean)	(s.d.)	(mean)	(s.d.)	(mean)	(s.d.)	(mean)	(s.d.)	(mean)	(s.d.)
Food & Tobacco	1.5	2.5	0.0	0.2	-0.4	4.2	0.8	3.2	-4.2	4.9
Textiles	0.4	0.3	-0.1	0.2	0.3	1.3	0.1	1.1	0.9	0.3
Apparel	0.1	0.9	0.1	0.4	0.2	0.9	-0.1	1.3	2.0	0.4
Wood Products	0.2	0.2	0.0	0.2	0.9	2.0	0.4	2.0	0.7	0.4
Furniture	0.3	0.3	0.1	0.2	1.0	2.0	0.2	1.0	1.0	0.3
Paper Products	0.2	0.5	0.0	0.1	0.4	0.6	0.1	0.8	-0.1	0.3
Printing & Publishing	0.1	0.2	0.0	0.3	0.4	1.1	1.1	1.4	0.1	0.1
Chemicals	0.1	0.1	0.0	0.2	1.2	1.8	0.3	1.3	1.2	0.3
Petroleum & Coal	0.1	0.6	0.0	0.4	-1.0	3.7	0.1	2.6	0.9	0.8
Rubber & Plastics	0.1	0.2	0.2	0.2	0.8	1.9	0.1	1.2	1.5	0.5
Leather Products	0.2	0.6	0.1	0.7	-0.8	3.7	0.3	1.7	0.7	0.5
Stone, Clay, & Glass	0.2	0.5	0.0	0.2	0.0	1.9	0.0	1.1	0.7	0.3
Primary Metals	0.2	0.5	0.1	0.2	0.0	1.9	0.4	1.6	0.7	0.3
Fabricated Metal	0.2	0.7	0.2	0.1	0.1	0.9	0.0	0.3	1.5	0.6
Industrial Machinery	0.2	0.8	0.2	0.3	2.0	3.3	0.0	0.6	2.1	1.0
Electronic Equip.	0.1	0.2	0.1	0.2	1.6	2.6	-0.1	1.2	3.5	1.2
Transportation Equip.	-0.1	1.5	0.1	0.4	0.2	1.8	0.1	2.1	1.3	1.4
Instruments	0.1	0.3	0.1	0.3	1.6	1.6	0.0	1.1	2.4	0.8
Miscellaneous	0.1	0.4	0.2	0.3	1.2	1.7	0.5	1.2	1.4	0.6

Gross Output Production Functions estimated by Wooldridge (2009) modification of Levinsohn and Petrin (2003) estimator.

Table 8: Aggregate Productivity Growth Decomposition
Baily, Hulten, & Campbell vs. Petrin-Levinsohn. U.S. Manufacturing 1977–1996

	Percentage Growth Rates of ...					
			APG=TE+RE		BHC=TE+BHC_RE	
	(1)	(2)	(3)	(4)	(5)	(6)
Year	Value Added	Aggregate Productivity (APG)	Technical Efficiency (TE)	Reallocation (RE)	BHC Productivity Index (BHC)	BHC Reallocation (BHC_RE)
1977	6.2	4.3	-0.5	4.8	-3.5	-3.0
1978	5.5	3.6	1.0	2.6	1.4	0.4
1979	6.4	5.4	3.1	2.3	4.4	1.3
1980	-6.2	-5.1	-3.9	-1.2	10.0	14.0
1981	2.7	2.8	-0.1	2.9	1.4	1.4
1982	-8.0	-4.5	-2.9	-1.6	-0.4	2.5
1983	5.9	5.9	4.2	1.8	-5.1	-9.3
1984	8.6	6.8	1.9	4.9	-3.9	-5.8
1985	0.5	0.3	-3.5	3.8	-3.1	0.4
1986	-0.3	-0.2	-4.3	4.0	-13.7	-9.4
1987	6.7	6.7	3.1	3.6	6.2	3.1
1988	5.1	4.4	2.1	2.4	11.5	9.5
1989	-0.7	-0.9	-2.3	1.4	3.3	5.6
1990	-3.1	-2.5	-0.4	-2.1	-9.1	-8.7
1991	-2.5	-2.0	-2.7	-0.7	-1.0	1.7
1992	3.4	3.7	3.0	0.7	5.5	2.5
1993	1.9	1.9	0.1	1.8	-20.3	-20.4
1994	6.9	6.5	3.9	2.6	2.3	-1.6
1995	4.7	4.2	2.2	2.0	10.2	8.0
1996	2.9	2.5	0.6	1.9	5.4	4.9
Mean	2.3	2.2	0.2	2.0	0.1	-0.1
s.d.	4.6	3.7	2.7	1.9	8.0	7.8

Gross Output Production Functions estimated by Wooldridge (2009) modification of Levinsohn and Petrin (2003) estimator.

Correlations of Annual Growth Rates

	APG	TE
TE	0.86	
BHC Index	0.14	0.27

Table A1: Percentage Growth Rates of Real GDP and Real Value-Added in Manufacturing, 1977-1996

		Real Value-Added in Manufacturing			
	(1)	(2)	(3)	(4)	(5)
Year	Real GDP	From NIPA	NBER-CES aggregates	Plant-level ASM (all)	Plant-level ASM (continuers)
1977	4.5	n/a	5.6	6.1	6.2
1978	5.0	n/a	5.2	4.7	5.5
1979	0.3	n/a	3.8	3.3	6.4
1980	-4.1	n/a	-4.5	-6.0	-6.2
1981	1.7	n/a	1.9	0.8	2.7
1982	-2.0	n/a	-3.5	-7.2	-8.0
1983	5.3	n/a	3.6	3.1	5.9
1984	6.6	n/a	5.8	11.0	8.6
1985	3.6	n/a	2.2	-0.3	0.5
1986	3.8	n/a	0.5	-0.3	-0.3
1987	2.5	n/a	9.2	7.0	6.7
1988	3.4	5.7	4.2	4.0	5.1
1989	2.5	1.3	-0.9	4.5	-0.7
1990	0.4	-1.1	-0.7	-1.5	-3.1
1991	-0.8	-1.4	-2.3	-3.9	-2.4
1992	2.6	3.3	7.2	9.9	3.4
1993	2.0	4.2	3.4	-1.4	1.9
1994	3.6	7.7	8.5	11.7	6.9
1995	1.7	4.5	11.1	12.0	4.7
1996	2.6	3.7	12.3	12.5	2.9
Mean	2.5	3.1	3.6	3.5	2.3
std. dev.	2.4	3.0	4.7	6.0	4.6

Correlations of Growth Rates

	GDP	NIPA MFG	NBER	All ASM plants
ASM continuers	0.78	0.97	0.78	0.79

Sources: Bureau of Economic Analysis, Annual Survey of Manufactures, NBER-CES productivity database, and authors' calculations.

Table A2a: Aggregate Productivity Growth Decomposition
Technical Efficiency and Reallocation. U.S. Manufacturing 1977–1996

	Percentage Growth Rates of ...			
			APG=TE+RE	
	(1)	(2)	(3)	(4)
Year	Value Added	Aggregate Productivity (APG)	Technical Efficiency (TE)	Reallocation (RE)
1977	6.2	4.3	0.8	3.4
1978	5.5	3.6	0.4	3.1
1979	6.4	5.4	1.4	2.6
1980	-6.2	-5.1	-5.3	0.7
1981	2.7	2.8	-0.1	1.6
1982	-8.0	-4.5	-4.1	-0.8
1983	5.9	5.9	4.8	1.2
1984	8.6	6.8	3.3	3.9
1985	0.5	0.3	-2.4	2.2
1986	-0.3	-0.2	-2.4	1.8
1987	6.7	6.7	4.1	1.9
1988	5.1	4.4	2.4	2.3
1989	-0.7	-0.9	-2.1	1.4
1990	-3.1	-2.5	-2.4	0.7
1991	-2.5	-2.0	-2.0	1.1
1992	3.4	3.7	2.7	1.5
1993	1.9	1.9	1.3	1.5
1994	6.9	6.5	5.1	2.0
1995	4.7	4.2	2.1	2.5
1996	2.9	2.5	0.7	3.0
Mean	2.3	2.2	0.4	1.9
s.d.	4.6	3.7	3.0	1.1

Gross Output Production Functions estimated by Levinsohn and Petrin (2003) estimator.

Table A2b: Aggregate Productivity Growth Decomposition
Technical Efficiency and Reallocation. U.S. Manufacturing 1977–1996

	Percentage Growth Rates of ...			
			APG=TE+RE	
	(1)	(2)	(3)	(4)
Year	Value Added	Aggregate Productivity (APG)	Technical Efficiency (TE)	(RE)
1977	6.2	4.3	0.6	3.7
1978	5.5	3.6	0.5	3.1
1979	6.4	5.4	2.0	3.4
1980	-6.2	-5.1	-3.9	-1.2
1981	2.7	2.8	-0.3	3.1
1982	-8.0	-4.5	-3.0	-1.5
1983	5.9	5.9	4.4	1.5
1984	8.6	6.8	2.4	4.4
1985	0.5	0.3	-2.0	2.3
1986	-0.3	-0.2	-2.3	2.0
1987	6.7	6.7	4.2	2.4
1988	5.1	4.4	1.9	2.5
1989	-0.7	-0.9	-1.7	0.8
1990	-3.1	-2.5	-1.4	-1.1
1991	-2.5	-2.0	-1.5	-0.5
1992	3.4	3.7	2.9	0.8
1993	1.9	1.9	1.3	0.6
1994	6.9	6.5	4.7	1.8
1995	4.7	4.2	2.4	1.8
1996	2.9	2.5	1.6	0.9
Mean	2.3	2.2	0.6	1.6
s.d.	4.6	3.7	2.6	1.7

Gross Output Production Functions estimated by OLS.

Table A3a: Decomposition of Reallocation Term (equation 9):
U.S. Manufacturing, 1977–1996

	Percentage Growth Rates of ...				
	(1)	(2)	(3)	(4)	(5)
		Reallocation "Gap" terms			
Year	Reallocation (RE)	Production workers	Non-Production workers	Materials	Capital
1977	3.4	0.8	0.2	1.5	0.8
1978	3.1	0.7	0.2	1.0	1.2
1979	2.6	0.1	0.2	1.0	1.4
1980	0.7	-1.1	0.1	0.1	1.6
1981	1.6	0.1	-0.0	-0.1	1.5
1982	-0.8	-1.5	0.1	-0.7	1.4
1983	1.2	0.2	0.1	-0.1	1.0
1984	3.9	0.8	-0.0	2.3	0.8
1985	2.2	0.1	0.0	0.6	1.5
1986	1.8	-0.1	0.1	0.4	1.3
1987	1.9	0.1	0.2	0.6	1.0
1988	2.3	0.5	0.1	0.8	0.8
1989	1.4	0.2	0.1	0.4	0.7
1990	0.7	-0.6	0.0	-0.2	1.4
1991	1.1	-0.2	0.2	-0.4	1.5
1992	1.5	0.3	-0.0	0.4	0.8
1993	1.5	0.2	0.1	0.3	1.0
1994	2.0	0.3	0.0	0.8	0.8
1995	2.5	0.0	0.2	1.2	1.1
1996	3.0	0.2	0.0	1.7	1.0
Mean	1.9	0.1	0.1	0.6	1.1
s.d.	1.1	0.6	0.1	0.7	0.3

Note: (1) = (2) + (3) + (4) + (5) (numbers may not add up exactly due to rounding.)
Gross Output Production Functions estimated by Levinsohn and Petrin (2003) estimator.

Table A3b: Correlations of Reallocation Terms

	Reallocation (RE)	Production workers	Non-Production workers	Materials	Capital
Reallocation	1.00				
Production Workers	0.68	1.00			
Non-production Workers	0.14	-0.08	1.00		
Materials	0.62	0.73	-0.04	1.00	
Capital	0.64	0.08	0.04	-0.05	1.00

Gross Output Production Functions estimated by Levinsohn and Petrin (2003) estimator.

Table A3c: Decomposition of Reallocation Term (equation 9): U.S. Manufacturing, 1977–1996

	Percentage Growth Rates of ...					
	(1)	(2)	(3)	(4)	(5)	(6)
		Reallocation "Gap" terms				
Year	Reallocation (RE)	Production workers	Non-Production workers	Materials	Energy	Capital
1977	3.5	0.9	0.3	1.5	0.2	0.2
1978	2.9	0.7	0.2	1.0	0.1	0.8
1979	2.1	0.0	0.3	0.9	0.0	0.8
1980	-0.2	-1.1	0.1	0.1	-0.2	0.9
1981	1.7	0.1	-0.0	-0.1	0.7	0.9
1982	-1.3	-1.5	0.0	-0.8	0.2	0.7
1983	1.4	0.2	0.1	-0.1	0.7	0.5
1984	4.4	0.9	-0.0	2.3	0.7	0.5
1985	2.0	0.1	0.0	0.6	0.4	0.8
1986	1.9	-0.1	0.1	0.5	0.6	0.7
1987	1.7	0.1	0.2	0.6	0.3	0.6
1988	2.5	0.6	0.1	0.8	0.6	0.4
1989	1.1	0.2	0.1	0.5	-0.1	0.4
1990	-0.1	-0.6	0.1	-0.1	-0.4	0.9
1991	0.7	-0.2	0.2	-0.4	0.0	1.2
1992	1.3	0.3	-0.0	0.4	0.1	0.5
1993	1.4	0.2	0.1	0.3	0.3	0.6
1994	2.2	0.4	-0.1	0.8	0.6	0.5
1995	2.2	0.0	0.2	1.2	0.2	0.6
1996	2.2	0.2	-0.0	1.7	-0.3	0.5
Mean	1.7	0.1	0.1	0.6	0.2	0.7
s.d.	1.3	0.6	0.1	0.8	0.3	0.2

Note: (1) = (2) + (3) + (4) + (5) + (6) (numbers may not add up exactly due to rounding.)

Gross Output Production Functions estimated by OLS

Table A3d: Correlations of Reallocation Terms

	Reallocation (RE)	Production workers	Non-Production workers	Materials	Energy	Capital
Reallocation	1.00					
Production Workers	0.82	1.00				
Non-production Workers	0.16	0.04	1.00			
Materials	0.71	0.71	0.03	1.00		
Energy	0.58	0.39	-0.26	0.12	1.00	
Capital	-0.34	-0.50	0.27	-0.50	-0.28	1.00

Gross Output Production Functions estimated by OLS

Table A4a: Aggregate Productivity Growth Decomposition
Technical Efficiency and Reallocation. U.S. Manufacturing 1977–1996
Percentage Growth Rates

Year	(1) Aggregate Productivity (APG)	(2) Technical Efficiency (TE)	(3) Reallocation (RE)	(4) Production worker "gap" term	(5) Non-Production worker "gap" term	(6) Capital "gap" term
1977	4.3	2.7	1.6	0.6	0.3	0.8
1978	3.6	1.3	2.3	0.7	0.3	1.3
1979	5.4	3.4	1.9	0.3	0.3	1.3
1980	-5.1	-6.3	1.2	-0.5	0.1	1.6
1981	2.8	1.2	1.5	0.1	0.0	1.5
1982	-4.5	-4.6	0.1	-1.3	0.1	1.4
1983	5.9	4.9	1.0	-0.3	0.1	1.2
1984	6.8	5.0	1.8	0.7	0.0	1.1
1985	0.4	-1.3	1.7	0.0	0.1	1.5
1986	-0.3	-1.8	1.5	0.0	0.1	1.4
1987	6.7	5.3	1.4	0.2	0.1	1.1
1988	4.4	3.0	1.4	0.5	0.0	0.9
1989	-0.9	-1.9	1.0	0.2	0.1	0.8
1990	-2.5	-3.2	0.7	-0.5	0.1	1.1
1991	-2.0	-2.7	0.7	-0.2	0.2	0.8
1992	3.7	2.9	0.8	0.1	-0.1	0.8
1993	1.9	1.0	0.9	0.0	0.0	0.9
1994	6.5	5.8	0.7	0.1	-0.1	0.8
1995	4.2	3.1	1.1	0.0	0.1	1.0
1996	2.5	1.4	1.1	0.2	0.0	0.9
Mean	2.2	1.0	1.2	0.0	0.1	1.1
s.d	3.7	3.5	0.5	0.5	0.1	0.3

Value-added Production Functions estimated by Levinsohn and Petrin (2003) estimator

Table A4b: Aggregate Productivity Growth Decomposition: Technical Efficiency and Reallocation. U.S. Manufacturing, 1977–1996 Percentage Growth Rates

Year	(1) Aggregate Productivity (APG)	(2) Technical Efficiency (TE)	(3) Reallocation (RE)	(4) Production worker "gap" term	(5) Non-Production worker "gap" term	(6) Capital "gap" term
1977	4.3	1.3	3.0	1.5	0.5	1.0
1978	3.6	0.3	3.3	1.4	0.6	1.3
1979	5.4	3.0	2.3	0.3	0.7	1.3
1980	-5.1	-5.4	0.3	-1.8	0.5	1.6
1981	2.8	1.2	1.6	-0.2	0.1	1.7
1982	-4.5	-2.6	-1.9	-3.1	-0.1	1.4
1983	5.9	5.0	1.0	-0.2	0.0	1.2
1984	6.8	4.1	2.8	1.5	0.1	1.1
1985	0.3	-1.3	1.7	-0.2	0.3	1.6
1986	-0.3	-1.4	1.2	-0.4	0.2	1.5
1987	6.7	5.3	1.4	0.3	0.0	1.1
1988	4.4	2.6	1.8	0.8	0.1	0.9
1989	-0.9	-2.0	1.1	0.1	0.0	1.0
1990	-2.5	-2.7	0.2	-1.1	0.1	1.2
1991	-2.0	-2.2	0.2	-0.9	0.2	1.0
1992	3.7	2.9	0.8	0.1	-0.3	0.9
1993	1.9	0.9	1.0	0.0	-0.2	1.2
1994	6.5	5.3	1.2	0.5	-0.2	0.9
1995	4.2	2.4	1.8	0.2	0.4	1.2
1996	2.5	1.0	1.4	0.3	0.0	1.1
mean	2.2	0.9	1.3	-0.1	0.2	1.2
s.d.	3.7	3.0	1.1	1.1	0.3	0.2

Value-added Production Functions estimated by OLS.

Table A5a: Correlations of Reallocation Terms
U.S. Manufacturing, 1977–1996

	Reallocation (RE)	Production workers	Non-Production workers	Capital
Reallocation	1.00			
Production Workers	0.78	1.00		
Non-production Workers	0.52	0.21	1.00	
Capital	0.31	-0.32	0.19	1.00

Value-added Production functions estimated by Levinsohn and Petrin (2003) estimator

Table A5b: Correlations of Reallocation Terms
U.S. Manufacturing, 1977–1996

	Reallocation (RE)	Production workers	Non-Production workers	Capital
Reallocation	1.00			
Production Workers	0.93	1.00		
Non-production Workers	0.52	0.21	1.00	
Capital	-0.10	-0.42	0.36	1.00

Value-added Production functions estimated by OLS

Table A6a: Summaries of Aggregate Productivity Growth Decompositions By 2-digit SIC Manufacturing Industry, 1977–1996

		(1)	(2)	(3)	(4)	(5)	(6)
		Technical Efficiency Growth (%)		Reallocation (% Growth)		Value-Added Share (%)	Positive Reallocation
SIC2	Industry	(mean)	(s.d.)	(mean)	(s.d.)	(mean)	(% of years)
20 & 21	Food & Tobacco Products	1.3	3.3	0.8	1.6	12.2	0.70
22	Textiles	1.8	5.6	1.0	1.3	2.3	0.85
23	Apparel	-0.5	3.2	1.8	1.6	2.3	0.80
24	Wood Products	-1.7	4.6	1.2	1.8	2.0	0.80
25	Furniture	-1.3	3.4	2.2	1.9	1.5	0.85
26	Paper Products	0.5	3.2	0.8	0.9	4.5	0.85
27	Printing & Publishing	-1.0	2.4	1.1	0.9	5.1	0.90
28	Chemicals	-0.6	4.4	2.0	1.4	11.0	0.95
29	Petroleum & Coal Products	1.8	14.1	0.9	5.1	1.8	0.65
30	Rubber & Plastics	0.8	4.0	2.0	1.5	3.7	0.90
31	Leather Products	0.4	4.8	-0.4	2.6	0.4	0.55
32	Stone, Clay, & Glass	0.5	4.4	0.8	2.1	2.7	0.75
33	Primary Metals	0.5	7.7	0.7	1.5	5.1	0.80
34	Fabricated Metal Products	-0.5	4.5	1.3	1.4	6.6	0.85
35	Industrial Machinery	1.7	3.9	3.3	3.8	10.7	0.90
36	Electronic Equipment	3.8	5.9	3.7	2.9	8.7	1.00
37	Transportation Equipment	-1.1	6.0	1.9	2.0	11.9	0.85
38	Instruments	-0.8	2.9	3.2	1.6	6.1	1.00
39	Miscellaneous	-1.3	4.8	2.5	1.6	1.4	0.95

Gross Output Production Functions estimated by the Levinsohn and Petrin (2003) estimator.

Table A6b: Summaries of Aggregate Productivity Growth Decompositions By 2-digit SIC Manufacturing Industry, 1977–1996

		(1)	(2)	(3)	(4)	(5)	(6)
		Technical Efficiency Growth (%)		Reallocation (% Growth)		Value-Added Share (%)	Positive Reallocation
SIC2	Industry	(mean)	(s.d.)	(mean)	(s.d.)	(mean)	(% of years)
20 & 21	Food & Tobacco Products	1.0	3.3	1.1	1.6	12.2	0.80
22	Textiles	2.0	4.9	0.8	1.3	2.3	0.70
23	Apparel	-0.2	3.1	1.5	1.7	2.3	0.85
24	Wood Products	-1.7	4.3	1.2	2.4	2.0	0.70
25	Furniture	-0.8	3.3	1.7	2.3	1.5	0.80
26	Paper Products	0.2	2.9	1.1	1.0	4.5	0.90
27	Printing & Publishing	-1.1	2.1	1.2	1.1	5.1	0.80
28	Chemicals	-0.5	4.2	1.9	1.5	11.0	0.95
29	Petroleum & Coal Products	2.0	13.3	0.9	4.7	1.8	0.70
30	Rubber & Plastics	0.8	3.6	1.9	1.8	3.7	0.85
31	Leather Products	0.6	4.9	-0.6	2.6	0.4	0.50
32	Stone, Clay, & Glass	0.8	3.8	0.6	2.5	2.7	0.75
33	Primary Metals	0.7	6.7	0.8	1.3	5.1	0.75
34	Fabricated Metal Products	-0.1	4.1	0.9	1.6	6.6	0.75
35	Industrial Machinery	1.9	3.6	3.0	4.1	10.7	0.85
36	Electronic Equipment	4.4	5.9	3.1	3.0	8.7	1.00
37	Transportation Equipment	-0.4	5.0	1.1	2.6	11.9	0.60
38	Instruments	-0.4	2.8	2.7	1.6	6.1	0.95
39	Miscellaneous	-0.7	4.6	1.9	1.6	1.4	0.85

Gross Output Production Functions estimated by OLS.

Table A7a: Summaries of Aggregate Productivity Growth Decompositions By 2-digit SIC Manufacturing Industry, 1977–1996

SIC2	Industry	(1) Technical Efficiency Growth (%) (mean)	(2) Technical Efficiency Growth (%) (s.d.)	(3) Reallocation (% Growth) (mean)	(4) Reallocation (% Growth) (s.d.)	(5) Value-Added Share (%) (mean)	(6) Positive Reallocation (proportion of years)
20 & 21	Food & Tobacco Products	0.9	3.4	1.2	0.8	12.2	0.95
22	Textiles	2.2	4.7	0.5	0.4	2.3	0.90
23	Apparel	0.5	3.4	0.8	0.7	2.3	0.90
24	Wood Products	-1.6	4.9	1.0	0.8	2.0	0.85
25	Furniture	-0.7	4.0	1.5	0.6	1.5	1.00
26	Paper Products	0.6	3.3	0.6	0.6	4.5	0.90
27	Printing & Publishing	-1.2	2.5	1.1	0.6	5.1	0.95
28	Chemicals	0.2	5.0	1.0	0.5	11.0	1.00
29	Petroleum & Coal Products	4.8	29.0	1.1	1.2	1.8	0.75
30	Rubber & Plastics	1.2	4.3	1.4	0.5	3.7	0.95
31	Leather Products	0.0	6.5	0.0	1.2	0.4	0.50
32	Stone, Clay, & Glass	0.6	5.0	0.8	0.5	2.7	0.95
33	Primary Metals	0.5	7.0	0.6	1.0	5.1	0.80
34	Fabricated Metal Products	-0.3	4.6	1.1	1.0	6.6	0.90
35	Industrial Machinery	3.5	5.7	1.7	1.4	10.7	0.90
36	Electronic Equipment	6.0	7.4	1.4	0.5	8.7	1.00
37	Transportation Equipment	-1.5	6.2	1.5	1.6	11.9	0.80
38	Instruments	0.2	2.9	2.0	0.9	6.1	0.95
39	Miscellaneous	-0.6	5.5	1.8	1.0	1.4	1.00

Value-added Production Functions estimated by the Levinsohn and Petrin (2003) estimator.

Table A7b: Summaries of Aggregate Productivity Growth Decompositions By 2-digit SIC Manufacturing Industry, 1977–1996

		(1)	(2)	(3)	(4)	(5)	(6)
		Technical Efficiency Growth (%)		Reallocation (% Growth)		Value-Added Share (%)	Positive Reallocation (proportion
SIC2	Industry	(mean)	(s.d.)	(mean)	(s.d.)	(mean)	of years)
20 & 21	Food & Tobacco Products	1.0	3.3	1.1	1.2	12.2	0.90
22	Textiles	2.1	4.3	0.6	1.1	2.3	0.75
23	Apparel	-0.1	3.3	1.5	1.3	2.3	0.90
24	Wood Products	-1.8	4.6	1.2	2.3	2.0	0.80
25	Furniture	-0.7	3.1	1.5	1.8	1.5	0.85
26	Paper Products	0.1	3.3	1.1	1.0	4.5	0.90
27	Printing & Publishing	-1.1	2.5	1.0	1.1	5.1	0.85
28	Chemicals	-0.7	5.1	1.8	1.1	11.0	1.00
29	Petroleum & Coal Products	4.5	29.0	1.4	1.7	1.8	0.85
30	Rubber & Plastics	0.7	3.9	1.9	1.4	3.7	0.90
31	Leather Products	0.7	6.5	-0.7	2.3	0.4	0.50
32	Stone, Clay, & Glass	0.7	4.2	0.7	1.5	2.7	0.85
33	Primary Metals	0.7	6.5	0.4	2.0	5.1	0.75
34	Fabricated Metal Products	-0.2	4.2	0.9	1.7	6.6	0.80
35	Industrial Machinery	3.5	4.6	1.7	2.7	10.7	0.85
36	Electronic Equipment	4.9	6.4	2.5	1.8	8.7	0.95
37	Transportation Equipment	-0.6	5.0	0.6	2.6	11.9	0.60
38	Instruments	0.5	2.9	1.6	1.7	6.1	0.80
39	Miscellaneous	-0.2	5.2	1.4	1.6	1.4	0.85

Value-added Production Functions estimated by OLS.

Table A7c: Summaries of Aggregate Productivity Growth Decompositions By 2-digit SIC Manufacturing Industry, 1977–1996

		(1)	(2)	(3)	(4)	(5)	(6)
		Technical Efficiency Growth (%)		Reallocation (% Growth)		Value-Added Share (%)	Positive Reallocation (proportion
SIC2	Industry	(mean)	(s.d.)	(mean)	(s.d.)	(mean)	of years)
20 & 21	Food & Tobacco Products	3.4	3.6	-1.4	3.8	12.2	0.40
22	Textiles	2.1	4.8	0.6	0.4	2.3	1.00
23	Apparel	0.4	3.4	0.9	0.7	2.3	0.90
24	Wood Products	-1.6	5.0	1.0	0.6	2.0	1.00
25	Furniture	-0.7	3.9	1.5	0.7	1.5	0.95
26	Paper Products	0.9	3.3	0.3	0.5	4.5	0.75
27	Printing & Publishing	-0.8	2.4	0.7	0.6	5.1	0.90
28	Chemicals	0.1	5.0	1.1	0.4	11.0	1.00
29	Petroleum & Coal Products	5.1	29.2	0.9	1.1	1.8	0.80
30	Rubber & Plastics	1.0	4.4	1.6	0.5	3.7	1.00
31	Leather Products	-0.1	6.5	0.1	1.1	0.4	0.50
32	Stone, Clay, & Glass	0.6	5.0	0.9	0.4	2.7	0.95
33	Primary Metals	0.4	7.5	0.7	0.6	5.1	0.85
34	Fabricated Metal Products	-0.3	4.7	1.1	0.8	6.6	0.95
35	Industrial Machinery	3.7	5.7	1.5	1.4	10.7	0.90
36	Electronic Equipment	5.3	7.5	2.1	0.6	8.7	1.00
37	Transportation Equipment	-0.9	6.4	0.9	1.6	11.9	0.70
38	Instruments	0.2	2.9	1.9	1.0	6.1	0.95
39	Miscellaneous	-0.3	5.4	1.6	0.8	1.4	0.95

Value-added Production Functions estimated by Wooldridge (2009) modification of Levinsohn and Petrin (2003) estimator.

Table A8a: Aggregate Productivity Growth Decomposition
Baily, Hulten, & Campbell vs. Petrin-Levinsohn. U.S. Manufacturing 1977–1996

	Percentage Growth Rates of ...					
			APG=TE+RE		BHC=TE+BHC_RE	
	(1)	(2)	(3)	(4)	(5)	(6)
Year	Value Added	Aggregate Productivity (APG)	Technical Efficiency (TE)	Reallocation (RE)	BHC Productivity Index (BHC)	BHC Reallocation (BHC_RE)
1977	6.2	4.3	0.8	3.5	1.4	0.5
1978	5.5	3.6	0.3	3.2	1.3	0.9
1979	6.4	5.4	1.3	4.0	3.4	2.0
1980	-6.2	-5.1	-5.3	0.2	3.1	8.5
1981	2.7	2.8	-0.1	2.7	3.4	3.3
1982	-8.0	-4.5	-4.1	-0.4	-21.0	-16.6
1983	5.9	5.9	4.8	1.1	-2.6	-7.4
1984	8.6	6.8	3.3	3.6	-0.2	-3.4
1985	0.5	0.3	-2.4	2.8	-9.1	-6.7
1986	-0.3	-0.2	-2.4	2.1	-20.3	-18.0
1987	6.7	6.7	4.1	2.6	0.5	-3.6
1988	5.1	4.4	2.4	2.1	5.8	3.4
1989	-0.7	-0.9	-2.1	1.2	2.3	4.3
1990	-3.1	-2.5	-2.4	-0.0	0.9	3.4
1991	-2.5	-2.0	-2.0	0.0	-9.9	-7.9
1992	3.4	3.7	2.7	1.0	-7.0	-9.7
1993	1.9	1.9	1.3	0.6	6.8	5.5
1994	6.9	6.5	5.1	1.4	1.8	-3.2
1995	4.7	4.2	2.1	2.1	6.5	4.6
1996	2.9	2.5	0.7	1.7	6.0	5.3
Mean	2.3	2.2	0.4	1.8	-1.3	-1.7
s.d.	4.6	3.7	3.0	1.3	8.1	7.4

Gross Output Production Functions estimated by Levinsohn and Petrin (2003) estimator.

Correlations of Annual Growth Rates

	APG	TE
TE	0.95	
BHC Index	0.43	0.41

Table A8b: Aggregate Productivity Growth Decomposition
Baily, Hulten, & Campbell vs. Petrin-Levinsohn. U.S. Manufacturing 1977–1996

	Percentage Growth Rates of ...					
			APG=TE+RE		BHC=TE+BHC_RE	
	(1)	(2)	(3)	(4)	(5)	(6)
Year	Value Added	Aggregate Productivity (APG)	Technical Efficiency (TE)	Reallocation (RE)	BHC Productivity Index (BHC)	BHC Reallocation (BHC_RE)
1977	6.2	4.3	0.6	3.7	2.7	2.1
1978	5.5	3.6	0.5	3.1	2.4	1.9
1979	6.4	5.4	2.0	3.4	4.4	2.4
1980	-6.2	-5.1	-3.9	-1.2	3.8	7.8
1981	2.7	2.8	-0.3	3.1	1.3	1.6
1982	-8.0	-4.5	-3.0	-1.5	-14.3	-11.3
1983	5.9	5.9	4.4	1.5	-1.5	-5.9
1984	8.6	6.8	2.4	4.4	1.2	-1.2
1985	0.5	0.3	-2.0	2.3	-4.7	-2.8
1986	-0.3	-0.2	-2.3	2.0	-15.3	-13.0
1987	6.7	6.7	4.2	2.4	0.1	-4.2
1988	5.1	4.4	1.9	2.5	4.0	2.1
1989	-0.7	-0.9	-1.7	0.8	1.4	3.1
1990	-3.1	-2.5	-1.4	-1.1	0.5	2.0
1991	-2.5	-2.0	-1.5	-0.5	-6.3	-4.9
1992	3.4	3.7	2.9	0.8	-4.0	-7.0
1993	1.9	1.9	1.3	0.6	6.6	5.4
1994	6.9	6.5	4.7	1.8	2.3	-2.4
1995	4.7	4.2	2.4	1.8	6.1	3.7
1996	2.9	2.5	1.6	0.9	8.7	7.2
Mean	2.3	2.2	0.6	1.6	-0.0	-0.7
s.d.	4.6	3.7	2.6	1.7	6.3	5.7

Gross Output Production Functions estimated by OLS.

Correlations of Annual Growth Rates

	APG	TE
TE	0.92	
BHC Index	0.42	0.43