ABSTRACT

Title of dissertation: CAPITAL-EMBODIED TECHNOLOGICAL CHANGE: MEASUREMENT AND PRODUCTIVITY EFFECTS

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This thesis develops new methods for measuring capital-embodied technological change and its effects on productivity. Rates of embodied technological change are necessary to properly measure the productive stock of capital. Results from the hedonic pricing literature have been used for this purpose, though not without controversy.

In this dissertation, I first develop an alternative, production-side approach to estimating embodied technological change. The method exploits the large variation in plant-level investment histories available in the Longitudinal Research Database at the U.S. Census Bureau. The empirical results show that the rate of embodied technological change (or, equivalently, obsolescence) in U.S. manufacturing from 1972-96 is between 7 and 17 percent. Any number in this range is substantially larger than price-based estimates.

A method of measuring embodied technological change via data on research and development (R&D) is also developed. I propose an index that captures the amount of R&D embodied in an industry's capital. Combining (and adjusting) data from the National Science Foundation and the Commerce Department, I construct a weighted average of the R&D done on the equipment capital that an industry purchases for 62 industries that span the U.S. private economy.

I find that the mean level of embodied R&D over 1972-96 is positively and significantly correlated with the estimates of embodied technological change that I obtained in the first part of the dissertation. Furthermore, embodied R&D has a positive and significant effect on conventionally-measured total factor productivity growth (as one would expect if conventionally-measured capital stocks do not account for embodied technology).

Estimates of embodied technological change are used to construct quality-adjusted measures of capital for the purpose of estimating industry-level labor productivity equations. These equations are incorporated into a full structural input-output forecasting model. Finally, the model's behavior in response to shocks in investment is analyzed.

# CAPITAL-EMBODIED TECHNOLOGICAL CHANGE:

# MEASUREMENT AND PRODUCTIVITY EFFECTS

by

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DEDICATION

I dedicate this dissertation to my wife-to-be, Page Tomblin, and my parents, John and Nancy Wilson for all of their support and encouragement.

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# Chapter 1

## Introduction

The hypothesis that much of technological progress is embodied in new capital goods, and therefore investment in new capital is necessary to foster productivity growth, is an old one -- tracing its roots at least as far back as Smith's *Wealth of Nations*, which attributed its source to the division of labor: "The invention of all those machines by which labour is so much facilitated and abridged, seems to have been originally owing to the division of labour" (Smith, 1776, p.9).[1] The basic hypothesis was refined and extended over time by Karl Marx, Joseph Schumpeter, and Robert Solow, among others.[2] Yet, obtaining independent measures of the rate(s) at which embodied (or "investment-specific") technological change has progressed has long eluded us. Absent knowledge of this rate, it is impossible to correctly measure the *productive capacity* of the economy's capital stock. The concept of the *productive capacity of capital*, or simply *productive capital* for short, is the theoretically correct (in terms of Neoclassical production theory) concept of capital to be used in production and productivity analyses. The productive capital stock, combined with information on the degree to which capital is being utilized, tells us the flow of capital services used in

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[1] See Scherer (1999), Chapters 2-4, for a discussion of the history of economic thought relating to technological change (particularly that which is embodied in machinery) and long-run productivity growth.

[2] In *The Communist Manifesto*, Marx argued that technological advances in machinery are a distinguishing feature of the "bourgeois" or capitalist system: "The bourgeoisie cannot exist without constantly revolutionizing the instruments of production, and thereby the relations of production, and with them the whole relations of society" (Marx and Engels, 1848).

the production process. The flow of capital services to production is one of the main determinants of labor productivity. Thus, understanding and predicting labor productivity relies on good measures of productive capital (as well as utilization rates).

Yet surprisingly little research has focused on the measurement of capital.[3] Perhaps this inattention is due to a low priority that the economics profession has in the past assigned to issues of data measurement in general. As Griliches (1994) argues, "It is the preparation skill of the econometric chef that catches the professional eye, not the quality of the raw materials in the meal, or the effort that went into procuring them." The situation does appear to be changing, however, at least as it pertains to capital measurement. Thanks in part to the rapid advances in equipment technology which have exacerbated and exposed the shortcomings of the current ways of measuring capital, researchers interested in productivity analysis and forecasting can no longer ignore these shortcomings in their empirical work. This recognition has created a strong and somewhat urgent need for a quantitative idea of the contribution these technological advances in equipment have had on productive capital and productivity (and more importantly, on their growth rates).

Everything presented in this dissertation was done with an eye towards satisfying this need. In Chapter 2, I develop a production-side approach to estimating equipment-embodied technological change as an alternative to the controversial price-side approach. The method exploits the large variation in plant-level investment histories available in the Longitudinal Research Database at the U.S. Census Bureau. The empirical results show that the rate of embodied technological change (or,

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[3] Unless otherwise indicated, *capital* will hereafter refer to *productive capital*.

equivalently, obsolescence) in the average U.S. manufacturing plant from 1972-96 is between 7 and 17 percent (depending upon the assumed specification). Any number in this range is substantially larger than price-based estimates, which has two important implications. First, the contribution of embodied technological change to economic growth is far greater than previously thought. Second, these estimates suggest that official investment price deflators do not adequately adjust for quality change.

A method of measuring embodied technological change via data on research and development (R&D) is developed in Chapter 3. I propose an index that attempts to capture the amount of R&D embodied in an industry's capital. Combining (and adjusting) data from the National Science Foundation and the Commerce Department, I construct a weighted average of the R&D done on the equipment capital that an industry purchases for 62 industries that span the U.S. private economy. I show that over three-quarters of the growth in embodied R&D over this period can be attributed to increased R&D done on equipment assets, with changes in asset mix explaining most of the remainder. I also find that the mean level of embodied R&D over 1972-96 is positively and significantly correlated with industry-level estimates of embodied technological change found using the plant-level manufacturing data. Furthermore, embodied R&D has a positive and significant effect on conventionally-measured total factor productivity growth (as we would expect if conventionally-measured capital stocks do not account for embodied technology). I use the estimated relationship between embodied R&D and estimates of embodied technological change to impute rates of embodied technological change for non-manufacturing industries.

In Chapter 4, I use the industry-level measures of embodied technological change to construct quality-adjusted measures of (productive) equipment capital stocks. I then use these equipment capital stocks to estimate labor productivity equations which are then incorporated into IDLIFT, a full structural input-output forecasting model developed and maintained by INFORUM.[4] A primary motivation for this dissertation was to provide labor productivity equations for IDLIFT that (1) follow Neoclassical production theory, (2) fit the industry-level time series data well, and (3) have sensible coefficients. Attempts to do this in the past have been unsuccessful, perhaps due to the mismeasurement of capital introduced by not accounting for embodied technological change. It is shown that accounting for embodied technological change does in fact result in labor productivity equations that fit the data as well or better than either similar equations using non-quality-adjusted capital stocks or the former, non-Neoclassically-based, productivity equations.

In Chapter 5, the estimated coefficients from the new labor productivity equations are then programmed into the IDLIFT model (in C++) and the model is run (now using these coefficients to determine the labor necessary to produce the model's forecasted level of output). Forecasts are generated and show that the new version of the model exhibits behavior in response to investment shocks that is more in line with neoclassical theory.

Chapter 6 concludes and suggests areas where further research is needed.

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[4] INFORUM stands for Interindustry Forecasting at the University of Maryland. It is a non-profit research center founded by Clopper Almon in 1967 which provides industry-level and macroeconomic forecasting and policy analysis. Douglas Meade has been largely responsible for the development of IDLIFT.

Chapter 2

**The Production-Side Approach to Estimating Embodied Technological Change**

*Note: This Chapter is a modified version of Sakellaris and Wilson (2000)*

## 1. Introduction

As noted in Chapter 1, the ultimate goal of this dissertation is to aid in the understanding and predicting of labor productivity by properly accounting for embodied technological change in our measures of capital. This chapter contributes to this goal by providing (1) an estimation framework with which to estimate embodied technological change and (2) a measure of how much of unexplained labor productivity growth (in manufacturing) is due to embodied technological change. By "unexplained labor productivity growth" here, I mean the part of labor productivity growth that cannot be explained by changes in the measured capital-labor ratio -- in other words, conventionally-measured total factor productivity (TFP) growth. So by providing a decomposition of TFP growth into embodied and disembodied technological change, I am able to provide a sense of the magnitude of the measurement error in labor productivity growth that is due to capital mismeasurement. In this chapter and the next, I make extensive use of the concept of TFP as a "measure of our ignorance" (Abramovitz, 1956) and therefore focus on accounting for some of TFP growth by mismeasurement of capital. I will return to explaining labor productivity per se in Chapter 4.

The seminal papers by Johansen (1959) and Solow (1960) argued that more recent vintages of capital may embody technological advances that make them "better" than older vintages. "Better", or equivalently "of higher quality", means displaying higher productivity after adjusting for wear and tear. An important implication of this idea is that investment is essential in reaping benefits from some part of technological progress. Recently, there has been significant research on the role of embodied technological change as a source of economic growth and fluctuations. Hulten (1992) shows that the failure to adjust capital for quality change has the effect of suppressing the quality effects into the conventional total-factor-productivity residual. He also finds that about 20 percent of the residual growth in quality-adjusted output of U.S. manufacturing is due to embodied technological change. Greenwood, Hercowitz, and Krusell (1997) find that embodied technological change accounts for close to 60 percent of the growth of output per hours worked in the U.S. economy.[5]

Both of these studies use Gordon's (1990) price index for producer durable equipment (PDE) and identify the embodied technological growth with the rate of decline of this index relative to a base index that is assumed not to contain any quality adjustment. This puts the rate of embodied technological change at about 3 percent for the years 1954 to 1990. Through a combination of techniques, including hedonics and matched models, Gordon created new price indexes for many types of durable goods as an alternative to the official price indexes reported in the Producer Price Indexes (PPI) and Consumer Price Indexes (CPI). However, as Gordon (1996) points out, the

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[1] It should be noted that Greenwood, el al. (1997) make a distinction between "embodied" and "investment-specific" technological change by defining the latter as *either* quality improvements in capital or decreases in the cost of producing capital, whereas they define embodied technological change as only quality improvements. We make no such distinction in this chapter and use these terms interchangeably. Our estimates of embodied technological change should reflect the combined effect of these two phenomena.

difference in the growth rates of his implied PDE index and the typical base index (usually either the PCE deflator or the NIPA PDE deflator) is not due to quality change alone. Some of the difference results from Gordon's corrections for traditional substitution bias present in the official indexes.

Furthermore, not all kinds of quality change are captured by the Gordon index. First of all, Gordon was only able to create new price indexes for durable goods for which sufficient data on model characteristics and prices was available. The Sears catalog was the primary source of this data. For a large number of goods, there simply was no data with which to improve upon the official price measurement.

Secondly, and more fundamentally, hedonic and matched models are simply inappropriate for a large number of goods. Consider the identifying assumptions of these models. A hedonic model identifies a set of characteristics that define a product, then prices a unit of each of those characteristics, and finally measures the price change associated with a bundle of characteristics holding constant the number of units. For example, it defines a computer as consisting of RAM, processor speed, hard disk space, size, and weight. It then estimates the prices of a megabyte of memory, a megahertz of processor speed, a megabyte of hard disk space, one less cubic inch, and one less pound. Finally, it compares the price of a 1 GB RAM, 1.5 Ghz CPU, 50 GB hard disk, 1200 $in^3$, 10 lb. "bundle" in 2001 with how much this bundle *would have cost* in 2000 had such a bundle been on the market. With a matched model, one would find a computer in 2001 that has exactly the same bundle of characteristics as a computer that *was* on the market in 2000, then calculate their price difference.

Christensen (1997) distinguishes between two types of technological change. A *sustaining* technological change is one which continues to push out the technological frontier along an established performance trajectory. A *disruptive* change, on the other hand, redefines the characteristics by which a product's performance is judged. Hedonic and matched models work well for goods, such as computers, that have a clear, definable, set of characteristics which exhibit a sustained trajectory of improvement over time. Goods characterized by disruptive technological change, however, have a rapidly changing characteristics set making comparisons along the dimensions of a single performance trajectory meaningless. For an economy consisting of a large number of these goods, comparing the productivity (a single "characteristic" by which all capital goods can be compared) of one year's goods to an earlier year's goods seems a far better solution.

In this chapter we propose an estimation framework that arrives at estimates of the rate of growth of embodied technological change directly from observed production, input and investment decisions at the plant level. If there are vintage effects (embodiment) then plants with relatively newer equipment should be more productive (controlling for materials, labor input and utilization of capital and labor). These effects may be estimated in a production function framework where the capital stock of equipment is not constructed using the perpetual inventory method. Instead, we include in the estimating equation the whole history of investment in equipment (all the vintages) deflated by a deflator that does not correct for any quality change.

The result that we obtain is that each vintage is about 12 percent more productive than the previous year's vintage (in the preferred specification and controlling for other productive inputs). This number is astounding compared to the commonly accepted 3 percent based on Gordon's (1990) series.[6] This has several important implications. First, the role of investment-specific technological change as an engine of growth is even larger than previously estimated. Second, existing producer durable price indices substantially mismeasure quality change, yielding biased measures of capital stock growth. Lastly, assuming Hulten and Wykoff's (1981) estimates of economic depreciation, which have since been adopted by the U.S. Bureau of Economic Analysis (BEA), are correct, our estimates suggest that obsolescence is the most important factor in the decline of a capital asset's value over time.

We evaluate the impact of embodied technological change on US manufacturing gross output growth between 1972 and 1996. We estimate that the effective capital stock of equipment grew about three times faster than commonly estimated and that the contribution of embodied technological change to US manufacturing total factor productivity growth was about two thirds.

## 2. A Two-Sector Model of Investment-Specific Technological Change[7]

[2] A notable exception is Bahk and Gort (1993) who also estimate a high rate of embodied technological growth.

[3] The exposition in this section follows Hornstein and Krusell (1996), Greenwood et al. (1997), and Hercowitz (1998). For clarity, we do not make a distinction here between structures and equipment investment, though in the empirical work this distinction will be crucial.

In order to formalize the concept of capital-embodied technological change we consider a two-sector model where one sector produces investment goods ( $\tilde{i}$ ) and the other produces consumption goods (c). Each good is produced using capital (k) and labor (l) as inputs according to the following production functions:

$$\tilde{i}_t = z_t q_t \tilde{k}_{\tilde{i},t}^{\alpha} l_{\tilde{i},t}^{1-\alpha} \tag{2-1}$$

$$c_t = z_t \tilde{k}_{c,t}^{\alpha} l_{c,t}^{1-\alpha} \tag{2-2}$$

where z is the level of technology common to both sectors whereas q is technological level specific to the investment sector[8]. A "~" denotes that the variable is defined in terms of efficiency units. For simplicity, α, the elasticity of output with respect to capital is assumed to be the same in both sectors.[9] Assume that all factors of production are perfectly mobile across sectors and that perfect competition holds in all markets. Then, as a result of factor price equalization, the price of investment goods relative to consumption goods is: $P_t^{\tilde{i}} / P_t^{c} = 1/q_t$. Thus, one may compute the

[4] Greenwood et al. (1997) discuss conditions under which the economy exhibits balanced growth with or without exogenous technological change.

[5] Hornstein and Krusell (1996) show the implications of allowing α to differ by sector.

rate of growth of investment-specific (capital-embodied) technological change from the rate of decline in the relative price of investment goods.

Figure 2-1 graphs the Personal Consumption Expenditures (PCE) deflator from the National Income and Product Accounts (NIPA) and an average equipment-investment price index for manufacturing. The latter is an average, over our plant-level sample, of the 3-digit industry equipment-investment deflators constructed by the Federal Reserve Board (FRB) using industry investment-by-asset type data from the BEA and Producer Price Indexes (PPI) for asset types[10]. Oddly enough, these two indexes grow about the same rate between 1972 and 1996[11]. Does this mean that there was no embodied technological change during this period? As we detail in the next section, several authors provided a negative answer arguing that the official price indexes for PDE grow too fast as a result of mismeasurement. They use, instead, equipment-investment price indexes constructed by Gordon (1990) to reflect quality change. However, the comparison of the above two price indexes is not the only way to ascertain the importance of embodiment. We provide below and in section (4) an alternative approach relying on data on produced output and utilized inputs .

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[6] The FRB industry-level deflators are matched to the plant-year records in our sample according to the 3-digit industry to which a plant belonged in that year. For each year between 1972 and 1996 (the investment years covered by our sample), we take the within-year, cross-sectional mean of the equipment-investment price deflators. Thus, for any particular year, this mean can be thought of as a weighted average of the FRB's 3-digit deflators where the weights are the fraction of our sample in each 3-digit industry. An unweighted average is nearly identical.

[7] However, the behavior is distinctly different in two subperiods. Between 1972 and 1981 equipment-investment prices rose 2.25 percent per year compared to consumption goods whereas from 1982 to 1996 they fell 1.67 percent per year.

Since the production function is homogeneous of degree one and the capital-labor ratio is equal across sectors one can write total output in terms of consumption goods as:

$$\frac{\tilde{i}_t}{q_t} + c_t = y_t = z_t \tilde{k}_t^{\alpha} l_t^{1-\alpha} \qquad (2\text{-}3)$$

Note that capital input, $\tilde{k}$, in the above expression is defined in efficiency units (i.e. in terms of investment goods):

$$\tilde{k}_t = (1-\delta)\tilde{k}_{t-1} + \tilde{i}_t \qquad (2\text{-}4)$$

where $\delta$ is the geometric rate of physical depreciation[12]. The above expression for total output demonstrates that this two-sector economy is equivalent to a one-sector economy where (disembodied) technological change is captured by $z_t$ and output saved as capital is enhanced (in terms of efficiency) by capital-embodied technological change, $q_t$. The society can only take advantage of this latter form of technological change by forgoing consumption and investing in capital.

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[8] This concept comes in many other names, for example, physical decay, or depreciation from use. It is not equivalent to economic depreciation.

To see this more clearly, define investment in terms of consumption goods: $i_t = \tilde{i}_t / q_t$. Then, the capital transition equation may be written as:

$$\tilde{k}_t = (1-\delta)\tilde{k}_{t-1} + i_t q_t \tag{2-5}$$

Once again, in order to construct the capital stock correctly one needs to adjust each vintage of investment for quality change that is due to investment-specific technological change. Equations (2-3) and (2-5) provide an alternative way of estimating embodied technological change, $q_t$, without the use of a price index for equipment investment. One may estimate the q series econometrically with plant level data, say, on output and current and past investment measured in terms of consumption in addition to data on labor input.

Equations (2-3) and (2-4) may be written equivalently as:

$$y_t = z_t q_t^{\alpha} k_t^{\alpha} l_t^{1-\alpha} \tag{2-6}$$

$$k_t = [(1-\delta)/(1+\gamma_t)] \cdot k_{t-1} + i_t \tag{2-7}$$

To see this, let $q_t/q_{t-1}=1+\gamma_t$ and $k_t = \tilde{k}_t/q_t$. The system of (2-6) and (2-7) provides an alternative way of constructing the capital stock and decomposing growth in output. Investment flows are unadjusted for quality improvement but depreciation gets augmented by a term, $1/(1+\gamma_t)$, that reflects obsolescence due to investment-specific technological change[13]. Note, however, that the residual in this decomposition known as total factor productivity (TFP) cannot be attributed to investment-neutral technological change, z, alone.

To drive home the point that there are many different but equivalent ways of measuring aggregate output and capital, and accounting for growth we present now yet another alternative to equations (2-3) and (2-4). Suppose that we measured aggregate output, Y, by summing investment goods production expressed in efficiency units and consumption goods production in consumption units. Indeed, this is the approach the NIPA attempts to follow. The national income accounting identity would then be written as:

$$\tilde{i}_t + c_t = Y_t = [(1-\mu_t) + \mu_t q_t] \cdot z_t \tilde{k}_t^{\alpha} l_t^{1-\alpha} \qquad (2\text{-}8)$$

where $\mu_t = \tilde{k}_{\tilde{i},t} / \tilde{k}_t$ is the fraction of aggregate capital stock, measured in efficiency units, devoted to investment goods production. Equivalently, $\mu_t$, may be measured as the ratio of the output of the investment sector, $\tilde{i}$, to total output, y, both measured in terms of consumption,

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[9] See Solow (1960) for extensive discussion of the implications of this result.

$$\mu_t = \frac{\tilde{i}_t / q_t}{c_t + \tilde{i}_t / q_t} \qquad (2\text{-}9)$$

The TFP that one obtains after applying the growth accounting decomposition with these measures of aggregate output (equation (2-8)) and capital stock (equation (2-4)) is a weighted average of the TFP in each of the two sectors where the weight is given by $\mu_t$.

## 3. Related Literature

One could classify the set of related papers into two camps. Most of the recent contributions use Gordon's (1990) quality-adjusted price indices for PDE in order to identify embodied technological change and then answer important questions related to economic growth or fluctuations in the U.S. The second camp contains older contributions that estimated embodied technological change using data on production and capital stock age using an approach due to Nelson (1964). We review these two camps briefly here and point out the main differences of our approach.

### *A. Price-Based Estimates of Embodied Technological Change*

Gordon (1990) is a major study aimed at correcting mismeasurement in equipment price indices due to quality change. He provides quality-adjusted price indices for 22 types of equipment and their components. Hulten (1992) was the first to use these series in order to identify embodied technological change. He constructed a share-weighted average of Gordon's indices as well as one for the corresponding price indices published by BLS. Taking the ratio of the two, he calculated the average annual growth rate of embodied technological change to be 3.44 percent for U.S. manufacturing during 1949-1983. As a result, he attributed about 20 percent of the residual growth of quality-adjusted manufacturing gross output to embodied technological change.

Various papers followed Hulten (1992) in using Gordon's data but differed in the methodology employed. Greenwood et al. (1997) argued that the baseline index for comparison should be the implicit price deflator for non-durable consumption goods. This had very little affect on their estimate of embodied technological change. Three other differences in methodology, however, were important. Greenwood et al. (1997) advocated that output not be adjusted for quality change, that value added data be used in place of gross output and that a general equilibrium approach be used that accounts for input growth due to embodied technological change. They found that embodied technological change contributed about 58 percent of all output growth in the U.S. between 1954 and 1990[14].

Hornstein and Krusell (1996) and Greenwood and Yorukoglu (1997), among others, note that the Gordon index points to a large increase in the rate of embodied technological change after 1973[15]. They argue that this increased technological change and the adjustment processes necessitated by it are largely responsible for the post-1973 measured slowdown in productivity growth.

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[10] Disembodied change provided the rest. The authors use the terminology investment-specific versus neutral technological change.

[11] This increase is about 25 percent. See, e.g., Hornstein and Krusell (1996) p. 231.

Greenwood et al. (2000) use Gordon's data to investigate the importance of embodied technological change for postwar U.S. aggregate fluctuations. They document a negative comovement between relative price of equipment and equipment investment. Their analysis suggests that about 30 percent of output fluctuations are due to shocks in this relative price.[16]

The practice of using Gordon's (1990) quality-adjusted price indices for PDE in order to identify embodied technological change is not uncontroversial. Gordon (1996) takes issue with it. He claims that differences between his indices and the official ones are not entirely due to quality change. He offers as an example the traditional substitution bias introduced by a change in the relative prices of goods. Furthermore, he continues, quality adjustment may arise for reasons unrelated to embodied technological change. For example, an energy price increase may lead consumers to shift from inexpensive and energy-inefficient air conditioners to expensive and energy-efficient ones. The latter are also more costly to produce at any given level of technology in the equipment-producing sector (denoted $q_t z_t$ in our two-sector model) and do not necessarily represent an increase in technology[17]. Given these problems, it seems fruitful to examine alternative methods of estimating embodied technological change.

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[12] There are several related papers. See Greenwood et al. (2000) pp. 110-2 for a partial review.

[13] Gort and Wall (1998) argue that estimates of embodied technological change based on Gordon (1990) may be substantially biased towards zero (pp. 1658-9). They also point out another problem with the group of studies applying this methodology. While they adjust investment flows for quality change, they implicitly assume that *economic* depreciation rates, derived from Hulten and Wykoff (1981) and incorporated in the NIPA, measure only physical decay. This is unlikely to be true as these measures also incorporate obsolescence, in principle.

*B. Production-Based Estimates of Embodied Technological Change*

Nelson (1964) developed a variant of Solow's (1960) embodiment model that illustrated the relationship between the rate of embodied technological change and the average age of capital. He showed that, to an approximation, the log of efficiency-adjusted capital ($\breve{k}$) is proportional to a time trend *plus* the difference of $\gamma a_t$ and the log of unadjusted capital (k), where $a_t$ is the average age of the unadjusted capital stock. Thus, a standard production function estimation (in logs) provides an estimate of embodied technological change by dividing the coefficient on average age by the coefficient on capital stock. Bahk and Gort (1993) study a sample of young manufacturing plants and find that a 1-year drop in average age is associated with between a 2.5 and a 3.5 percent rise in the plant's gross output (See their Table 1 and p. 571). Assuming a one-sixth share weight for capital in the production function of gross output, these results correspond to a 15-21 percent annual rate of growth of embodied technological change. This is five to seven times higher than the price-based estimates discussed above.

However, Bahk and Gort (1993) make the dubious assumption that maintenance outlays offset the effect of physical decay on the capital stock. Their capital stock construct is the sum of gross investments of all vintages without any adjustment for physical depreciation[18]. Their estimates are best regarded as describing the joint impact

[14] While they admit that "this assumption is only at best an approximation of reality" (p.566) they do not provide concrete supporting evidence for it.

of physical depreciation and embodiment. Our view is that physical decay occurs at a rate higher than zero.

For the sake of comparison, we also estimate the rate of embodied technological change using the average vintage specification. However, as discussed in Section 6 below, the Nelson approach relies on an approximation which is unreasonable for our data. Our framework is more general than Nelson's (1964) and is described in the next section[19].

## 4. Our Methodology

The elusive holy grail of the embodiment literature has been independent estimates of embodied technological change. Our approach is to estimate that from production data. It involves exploiting the cross-sectional and time-series variation in plant-level historical investment distributions in order to estimate the relative levels of technology embodied in particular vintages of investment.

A simple example will help illustrate the basic concept. Consider two plants, A and B, both born in 1980 and observed continuously until 1989 (inclusive). Plant A expended 55% of its lifetime (up to 1989) investment in 1980 and 5% in each year thereafter. In contrast, plant B invested 55% in 1989 and 5% in each prior year. The plants are otherwise identical. One can exploit the variation in these two plants' vintage distributions in investment (net of physical decay) to estimate embodied technological change by comparing their output in 1989. Doms and Dunne (1998)

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[15] A similar approach has been used before in a different but related context. Mark Doms (1996) applied the approach to a sample of "mini-mill" steel plants in order to estimate the physical depreciation schedule.

provide empirical evidence of this kind of variation in investment. They find that over a 17-year period, 50% of the average plant's investment is concentrated in 3 years (not necessarily consecutive). Furthermore, lumpy investment activity is not perfectly synchronized across plants.

We now formalize the production approach. Consider a Cobb-Douglas function for the production of plant output:

$$y_{it} = \beta \cdot l_{it} + \theta \cdot m_{it} + \alpha \cdot \log(U_{it}^{J} J_{it}) + \eta \cdot \log(U_{it}^{S} S_{it}) + \zeta_{it} \qquad (2\text{-}10)$$

where y is gross output, l is labor hours, S is the structures capital stock, m is materials (including energy expenditures), J is the equipment capital stock, i indexes plants, and t indexes year[20]. Lowercase letters denote natural logs. The disturbance term, $\zeta_{it}$, captures stochastic shocks to disembodied technology. It may contain both an aggregate and an idiosyncratic component. Equation (2-10) is the plant-level analogue of the aggregate production function (2-3).

$U^J$ and $U^S$ in equation (2-1) denote that the utilization rates of equipment and structures capital, respectively. To measure utilization, we follow Petropoulos (1999) who shows that under certain reasonable conditions, the intensity of a plant's energy usage can be used as a proxy for capital utilization. Specifically (suppressing year and plant subscripts), we assume:

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[16] All variables are in constant dollars unless stated otherwise.

$$U^J = (E/J)^{\frac{1}{\tau_J}} \quad \text{and} \quad U^S = (E/S)^{\frac{1}{\tau_S}} \tag{2-11}$$

where E denotes energy expenditures (fuel plus electricity). For purposes of identification, we assume that $\tau_J = \tau_S = \tau$. Substituting these expressions into the production function (2-1) and rearranging, we obtain

$$\begin{aligned} y_{it} &= \beta \cdot l_{it} + \theta \cdot m_{it} + [\alpha(\tau - 1)/\tau] \cdot \log(J_{it}) \\ &\quad + [\eta(\tau-1)/\tau] \cdot \log(S_{it}) + [(\alpha+\eta)/\tau] \cdot e_{it} + \zeta_{it} \end{aligned} \tag{2-12}$$

where e denotes ln(E). Observable measures of q, l, m, and e can be readily constructed using variables in the LRD and price deflators from the NBER-CES Productivity Database (hereafter, NBER-CES). The construction of variables is described in Appendix A.

In this chapter, we focus on the estimation of the rate of embodied technological change in *equipment* capital. Therefore, plants' structures capital stock is calculated according to the traditional perpetual inventory definition (see Appendix A) using historical structures investment from the LRD, price deflators from NBER-CES, and physical decay data from the FRB. Equipment capital, on the other hand, is a parameterized stream of past real equipment investment (net of physical decay):

$$J_t = \sum_{s=1}^{T} I_{t-s} D_{t,t-s} \phi_{t-s} \quad (2\text{-}13)$$

where T is the age of the plant, $I_{t\text{-}s}$ is real equipment investment of vintage t-s capital goods, $D_{t,t\text{-}s}$ is the fraction of one dollar's worth of vintage t-s investment that is still used in production in year t, and $\phi_{t\text{-}s}$ is the level of embodied technology in equipment capital of vintage t-s relative to some numeraire year's technology[21][22]. This equation is analogous to equation (2-5) in the 2-sector model. Equation (2-13) incorporates a one-year time-to-build assumption; that is, new investment is not put into operation until the following year. It takes time to build because of actual assembly requirements or because time is needed to train workers on how to use the new equipment[23].

Substituting equation (2-13) into (2-12) yields the estimating model. Given the large number of parameters and the non-linearity of the model, we found that obtaining estimates (precise or otherwise) of $\phi_{t\text{-}s}$ was not possible in all but the most parsimonious of specifications. Thus, for the regressions reported in this chapter, we

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[17] In terms of the two-sector model we described earlier, $\phi_t$ is the ratio of $q_t$ to $q_0$ where 0 refers to the numeraire year.

[18] We assume that investment in vintage t-s capital goods is synonymous with new investment in year t-s. This is incorrect to the extent that there is investment in used capital of earlier vintages. Unfortunately, data on the vintage of a plant's used investment is not available in the LRD. This should have little effect on our results since used investment is typically a negligible part of total investment (new plus used).

[19] We estimated some specifications allowing no time to build but assuming that investment is distributed evenly throughout the year so that, on average, six months' worth of total investment in the newest vintage is used at any one time. The estimates of $\gamma$ are uniformly higher under this specification.

simplify by assuming a constant geometric rate of embodied technological change. This changes the specification of J to:

$$J_t = \sum_{s=1}^{T} I_{t-s} D_{t,t-s} (1+\gamma)^{t-s-t_0} \qquad \text{(2-14)}$$

where $\gamma$ is the rate of embodied technological change and $t_0$ is the numeraire year in which the level of embodied technology is normalized to 1. We choose 1996, the last year of our data, as the numeraire year.[24]

*A. Discussion of Variable Capital Utilization*

Unmeasured variation in the intensity with which plants utilize capital may lead to biases in production function estimation. We avoid this pitfall by proxying for capital utilization with energy use[25]. The parameter $\tau$ in the assumed functional form (2-11) is the elasticity of the rate of energy use with respect to capital utilization. It

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[20] Equations (2-13) and (2-14) provide a way of aggregating vintages that embody different technology levels. Fisher (1965) shows that a necessary and sufficient condition for the existence of a capital aggregate are that the marginal rate of substitution between any pair of inputs within the aggregate be independent of the inputs outside the aggregate. Under constant returns to scale, as Solow (1960) showed, this condition requires that 1) production with each vintage be additively separable, 2) total factor productivity be the same across all vintage production functions at a given year, and 3) investment in a "better" vintage of equipment is equivalent to a larger amount" of investment measured in constant quality.

[21] This approach was suggested by Jorgenson and Griliches (1967) and followed by Burnside, Eichenbaum, and Rebelo (1995) for industry-level estimation and Petropoulos (1999) for plant-level estimation, among others. See Fernald and Basu (1999) for pitfalls arising from unmeasured factor utilization.

allows for energy use being proportional to capital services (UJ or US, as in Burnside, Eichenbaum, and Rebelo, 1995) when $\tau = 1$. For values of $\tau > 1$ the marginal cost of capital services increases faster with utilization than with capital stock and at the extreme ($\tau = \infty$) there is no variation in utilization as it is too expensive. Similarly, when $\tau < 1$ the marginal cost of capital services increases slower with utilization than with capital stock and at the extreme ($\tau = 0$) any variation in utilization is achieved by an infinitesimal variation in energy use.[26]

*B. Discussion of Physical Depreciation Assumptions*

Our estimates of the rate of growth of embodied technological change rely importantly on accurate measures of physical depreciation. This is the part of economic depreciation that is due to wear and tear resulting from using the asset in production. We do not use the exponential depreciation rates produced by BEA, which are largely based on the estimates of Hulten and Wykoff (1981), as these reflect both physical deterioration and obsolescence. Instead, we employ the methodology used by BLS and FRB in constructing capital stocks adjusted for the effects of physical depreciation. This methodology is described in Appendix A.

There are two important differences. First, the FRB-BLS methodology results in an age-efficiency schedule that is vastly different from geometric, especially in the early part of an asset's life. Second, the implied rate of depreciation is much lower than that for BEA. These features can be seen in Figure 2-2 which graphs the average

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[22] Petropoulos (1999) argues that often plants increase capital utilization by "dusting off" older, less efficient machines. Then, increases in utilization would require increasing rates of energy use per unit of capital utilized ($\tau > 1$).

depreciation schedule by age in our primary sample for each source of depreciation data. Specifically, for the FRB-BLS depreciation data, this is the average by age (s) over all years (t) and plants (i), of the $D_{i,t,t-s}$ introduced in equation 13[27]. The same is done for the $D_{i,t,t-s}$ data that is implied by the BEA depreciation rates according to the identity $D_{i,t,t-s} = (1-\delta_s^{BEA})^{t-s}$. Lastly, the depreciation schedule implied by a 12% geometric rate is provided as a frame of reference. In the empirical section, we explore the implications for our estimates of $\gamma$ of different assumptions about physical depreciation.

## 5. Data

The plant-level data we use come from the Longitudinal Research Database (LRD), which is housed at the U.S. Census Bureau's Center for Economic Studies. The LRD consists of annual data on U.S. manufacturing establishments collected in the quinqennial Census of Manufactures (CM) and the Annual Survey of Manufacturing (ASM). At this time, it covers 1963, 1967, and 1972-96. The construction of the variables that we use in our analysis is described in detail in Appendix A.

We construct several data samples with which to estimate equation (2-3). Our primary sample, which we term the "POST72A" sample, is an unbalanced panel consisting of all plant-year observations from plants born in or after 1972 that survived for at least four consecutive years (including the birth year), with the last possible

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[23] Though $D_{i,t,t-s}$ has a plant subscript, this variable is the same for all plants within a 3-digit industry.

observation year being 1996. Thus, a single plant may have multiple observations in our sample, provided that we continuously observe the plant's equipment investment for every year from birth until the current observation year. Observations from plants born prior to 1972 are excluded as we cannot observe their entire investment history. These missing investment variables would likely have caused substantial biases in estimating the relative efficiency of different vintages of investment.

Since we exclude plants born prior to 1972 there is a concern that our results may not be representative of the entire manufacturing sector. There is evidence (e.g. Dunne, 1991) that large, old plants invest in more technologically advanced equipment than do young, small plants. Thus, for purposes of comparison, we construct a sample containing all observations in POST72A and, in addition, plants born prior to 1972 for which we observe "most" of their investment history. Specifically, we include observations in which cumulative observed equipment investment as of the current observation year is at least 80% of the current book value of equipment assets. Assuming equipment assets are retired on a first-in-first-out (FIFO) basis, this will ensure that though capital is still understated, no more than 20% of equipment currently in place is unobserved. Again we include only observations for plants that have survived at least 4 consecutive years. We call this sample "SCREEN."[28]

We keep only observations from plants that have survived at least four consecutive years in an effort to avoid two possible problems. First, the factor

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[24] The 80% cut-off value was chosen based on an analysis of the cross-sectional distribution of the ratio of cumulative observed investment to current book value for each year in the LRD. This screen/cut-off applies to plant-year observations, that is earlier observations for a plant may be screened out while later ones may be kept.

elasticities, particularly for capital, in the first three years of a plant's operations have been shown to be significantly different than those in later years (see Bahk and Gort (1993)). In fact, the elasticity of output with respect to capital is often found to be statistically insignificant in the first few years. Bahk and Gort attribute this phenomenon to learning by doing. Second, data is imputed for a substantial portion of any given year's newly-born plants (with the exception of data on industry, employment, and payroll). Thus, data from the first year of plants is fraught with measurement error. Since we utilize the entire investment history of a plant, we are not immune to the measurement error introduced by imputation of the first year's equipment investment. However, the share of investment that is imputed becomes smaller and smaller as the plant ages and thus, it is hoped, its impact should be minimal by the fourth year.

There is a trade-off between the improved data reliability, achieved by excluding observations from the first three years of a plant's operations, and the potential introduction of a sample selection bias by only selecting observations that were "successful" enough to survive at least four years. To ensure that our results are not unduly affected by this type of bias, we also create a sample, called POST72B, which is a superset of POST72A and relaxes the restriction that plants survive at least four years. Due to the imputation of data for the first year of many plants, we still exclude observations from the birth year. This should almost entirely eliminate the possibility of a "survivorship" bias in the regressions run using this sample since plants are allowed to exit after their second year.

For a final alternative to our primary sample (POST72A), we also construct a balanced panel sample consisting of 1975-96 observations from plants that were continuously in the LRD from 1972-96 (but not necessarily born between 1972-96). This was done in order to facilitate comparison to the rest of the literature on plant behavior since similar balanced panels are frequently used. Following our previous discussion, we expect the 1972-96 panel to suffer greatly from problems of omitted variables bias (due to unobserved pre-1972 investment) and sample selection bias.

*A. Is our Sample Representative of Manufacturing?*

The POST72A sample seems to be the best alternative when trying to jointly minimize the potential biases discussed above. It consists of a total of 96,846 plant-year observations covering 24,404 plants. Appendix A provides detailed comparison of POST72A to the other data sets we use and to the aggregate manufacturing sector (according to published Census data). In terms of the dynamic behavior of its plants, this sample is quite representative of the manufacturing sector as a whole. The average growth rates of investment and employment are quite similar over the 1975-96 period. This is true even though the sample, due to the nature of the LRD, consists of plants that are larger, on average, than the typical manufacturing plant (in terms of gross shipments, employment, or investment) as aggregate activity is primarily shaped by large plants. The sample distribution of shipments across 2-digit SIC industries is also quite representative of manufacturing though there is a tendency to under-represent mature-plant industries such as Petroleum and over-represent young-plant industries such as Communications.

## 6. Results

In this section we present the results of our estimation. We employ non-linear least squares (NLLS) with a heteroskedasticity- and autocorrelation-consistent (HAC) variance-covariance matrix. The HAC VC matrix is necessary because autocorrelation of the errors is likely due to the fact that the same plant can have multiple observations in our sample. All regressions include year and industry dummies as well as industry-specific time trends. In addition, we include a dummy variable, which we call *Multi*, indicating whether the plant is part of a firm that operates multiple plants. Table 2-1 contains our main results.

Initially, we do not allow for variable capital utilization by setting $\tau=\infty$. As may be seen in column (A), the rate of growth of embodied technological change, $\gamma$, is estimated to be a little under 8 percent. This is higher than the rate calculated in the price-based approaches using Gordon's (1990) data. The coefficient on *Multi* indicates that plants in a multi-establishment firm have on average 8.7 percent higher TFP than single-establishment firms, other things equal. This is consistent with past results in the plant-level literature (see, e.g., Baily, Hulten, and Campbell (1992)). The estimated factor elasticities are quite close to observed factor shares with the exception of the capital coefficients, which are a bit lower.[29]

The data seem to support allowing for variable capital utilization, at least as proxied by energy use. As may be seen in Column (B), the estimate of $\tau$ is 2.08 (with a

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[25] Allowing factor elasticities to vary by industry yields a slightly lower estimate of $\gamma$ of 0.055 (0.028). However, many of the estimated elasticities are nonsensical, particularly those for structures. It appears allowing industry-varying elasticities may be asking too much from the data and therefore we maintain the assumption of common elasticities for the regressions to follow.

standard error of 0.09). This value implies that the marginal cost of capital services (*UJ* or *US*) increases faster with utilization than with capital stock. In particular the Leontief assumption employed by Jorgenson and Griliches (1967) and Burnside et al. (1995), $\tau$=1, is rejected by our data. The estimated elasticities of capital and labor change in the direction one would expect if plants vary their capital utilization significantly in response to shocks. Not taking such variation into account creates an omitted variable likely to be positively correlated with employment (biasing its coefficient upward) and negatively correlated with the stock of capital (biasing its coefficient downward)[30].

[26] For plant-level evidence on these patterns of correlation see Sakellaris (2000).

## Table 2-1 Main Results

| Parameter | A | B | C | D |
|---|---|---|---|---|
| $\gamma$ | 0.077 (0.029) | 0.169 (0.049) | 0.116 (0.060) | 0.271 (0.059) |
| Intercept | 2.298 (0.049) | 2.421 (0.054) | 2.369 (0.080) | -1.183 (1.077) |
| Multi | 0.087 (0.008) | 0.079 (0.008) | 0.080 (0.008) | 0.080 (0.005) |
| $\beta$ | 0.344 (0.005) | 0.322 (0.005) | 0.319 (0.005) | 0.318 (0.002) |
| $\Theta$ | 0.545 (0.005) | 0.531 (0.005) | 0.529 (0.005) | 0.529 (0.002) |
| $\alpha$ | 0.078 (0.003) | 0.108 (0.005) | 0.114 (0.005) | 0.114 (0.002) |
| $\eta$ | 0.008 (0.002) | 0.020 (0.004) | 0.018 (0.004) | 0.019 (0.002) |
| $\tau$ | | 2.076 (0.091) | 2.219 (0.105) | 2.232 (0.050) |
| Adjusted $R^2$ | 0.926 | 0.927 | 0.927 | 0.927 |

A: Base regression (does not allow for capital utilization or learning-by-doing effects).
B: Adjusts for capital utilization using energy expenditures (see equation 11).
C: Full specification (adjusts for capital utilization and includes variables capturing learning-by-doing effects associated with investment spikes).
D: Average vintage regression (see equation 15).
Note: Regressions A-D also included year and industry dummy variables as well as industry-specific time trends. The coefficients on these are not shown in order to conserve space. They can be obtained from the authors upon request.

As may be seen in (B) controlling for variation in utilization reduces the coefficient of labor by 2 percent while it increases the sum of the coefficients of capital by more than a third bringing the ratio of the elasticities of labor and capital to about 2 to 1, as expected. Returns to scale are estimated to be 0.98 which is not statistically significantly different from one. The estimate of $\gamma$ is much higher now at 17 percent. This implies a vastly higher rate of embodied technological change than is usually considered.

### *A. Learning Effects*

Several papers since Arrow (1962) have suggested that the installation of new equipment embodying improved technology may involve significant subsequent investments in training workers as well as experimentation in the organization of production. These would tend to reduce productivity initially while raising it eventually and Arrow (1962) termed this process "learning by doing".[31] Ignoring such learning effects might bias our estimate of $\gamma$, though the direction of the bias is not clear. To explore the extent of such problems we repeat our estimation including an indicator of whether the plant undertook an equipment-investment spike together with seven lags of it.[32] Our idea is that spikes are associated with most instances of an introduction of a new and "better" vintage of technology and the inclusion of the spike indicators should control for learning effects on productivity. As may be seen in column C of Table 2-1, the estimate of $\gamma$ is about 12 percent and the rest of the coefficients do not change much.[33]

*B. Average Vintage Effect*

In Section 3 we mentioned that an alternative production-based approach which obtains $\gamma$ via the estimated coefficient on average age or vintage of capital is due to

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[27] See Greenwood and Jovanovic (1998) for an extensive analysis of the macroeconomic implications of learning-by-doing as well as references to some recent work.

[28] We identify a spike with observations of equipment investment to capital ratios greater than 0.20. See Power (1998), Doms and Dunne (1998), Cooper, Haltiwanger, and Power (1999) and Sakellaris (2000) for justification of using this definition at the plant level.

[29] The coefficients on the spike indicators show an approximately 6% drop in productivity in the first year after a spike with slow recovery thereafter.

Nelson (1964). In the most parsimonious case where one does not allow for unobserved utilization or learning effects, this approach leads to the following specification (ignoring the constant, the error term, and time and industry dummies):

$$y_{it} = \rho \cdot t + \beta \cdot l_{it} + \theta \cdot m_{it} + \eta \cdot s_{it} + \alpha \cdot j'_{it} + \alpha \cdot \log(1 + \gamma \overline{V}_{it}) \qquad (2\text{-}15)$$

where j´ is log equipment capital *unadjusted* for embodied technological change (i.e. j´ is just j from equation (2-14) with $\gamma$ set equal to zero) and $\overline{V}$ is the average vintage of equipment for plant i in year t. Generally, $\gamma\overline{V}$ is assumed to be close to zero allowing the last term in (2-15) to be approximated by $\alpha\gamma\overline{V}_{it}$. In our sample, however, the mean (over all plant-year observations) average vintage is approximately 12 (corresponding to 1984). The product of 12 and even a very small $\gamma$, say 0.01, will still be far from zero suggesting that serious specification errors are likely when we estimate (2-15).

In fact, as shown in column (D) of Table 2-1, the Nelson method yields the rather implausible estimate of 27 percent for $\gamma$ which is significantly different from the 12 percent found using our method.

### *C. Industry-specific time trends*

We are concerned that dynamic behavior of output, inputs, and disembodied technological change may differ substantially across industries. A prominent example is the computer sector which has enjoyed rapid growth in its productivity relative to other manufacturing industries and a correspondingly rapid relative decline in its price index. In order to control for this we include a set of industry-specific time trends in each of our regressions. All industry trends were between ±1 percent with the important exceptions of computers (8.3%) and communication equipment (3.3%).[34] Given that the computer industry has such a high rate of disembodied technological change, it is natural to wonder whether the computer industry is the primary driver of our high estimates of $\gamma$. Omitting the computer industry decreases our estimate from 0.116 to 0.070 (with a std. error of 0.053). Thus, it appears the computer industry is *a* but probably not *the* primary driver of economy-wide embodied technology.

*D. Alternative Depreciation Assumptions*

The estimate of $\gamma$ depends crucially on our assumption for physical depreciation. We now explore the implications of alternative assumptions on depreciation. We go through two hypotheses that imply that current methods of capital stock construction are valid. Our departure point is the observation that the PCE deflator and the official equipment-investment price index do not display very different trends for manufacturing (see Figure 2-1).

The first hypothesis is that: a) there is no embodied technological change and as a result PCE and official equipment-investment deflators are correctly measured and roughly similar over the 25-year period studied here, and b) the BEA geometric rates are accurate measures of physical depreciation alone (despite the fact they differ greatly

[30] These estimates refer to the regression in Column C though the corresponding estimates from the other regressions are quite similar. We were able to reject the hypothesis that industries do have a common time trend via a Wald test at a 99% level of confidence. The F-statistic is 84.5, far greater than the 99% critical value of 1.8.

from the FRB patterns of physical depreciation). Hypothesis 2 is that: a) there is embodied technological change, b) whereas the consumption goods price is correctly measured by the PCE deflator, the official equipment-investment deflator does not adjust at all for embodied technological change, and c) the BEA geometric rates correctly measure the combined effect of physical depreciation and obsolescence.

Unfortunately, the above two hypotheses are observationally equivalent with our data and methodology. To evaluate whether either could be true we perform two experiments, the results of which are shown in Table 2-2. In columns A and C we impose the BEA rates in place of the schedules for $D_{t,t-s}$ obtained with the BLS-FRB methodology. An alternative check is to impose zero depreciation and see whether the estimate of $\gamma$ is approximately equal to the average BEA rate for our sample, 12%. The results of this are shown in Columns B and D. Columns A and B correspond to the baseline specification which does not control for variable capital utilization or learning effects, whereas Columns C and D corresponds to our preferred specification which does control for these effects. When BEA rates are used, the estimates of $\gamma$ are insignificantly different from zero providing support for these hypotheses. The estimates in Columns B and D, however, are inconsistent with either of the hypotheses. In our preferred specification the estimate of $\gamma$ is 24.5 percent with a standard error of 6.5 percent, which is statistically different from 12.1 at the 10% level of significance. The evidence is less contradictory to these hypotheses in the baseline specification that does not control for variable capital utilization. Thus, the strength with which we can reject these hypotheses depends upon which specification one prefers.[35]

**Table 2-2 Results with Alternative Depreciation Assumptions**

| Parameter | A | B | C | D |
|---|---|---|---|---|
| $\gamma$ | 0.019 (0.025) | 0.153 (0.029) | 0.005 (0.042) | 0.245 (0.065) |
| Intercept | 2.218 (0.047) | 2.417 (0.024) | 2.229 (0.034) | 2.534 (0.081) |
| Multi | 0.087 (0.008) | 0.086 (0.008) | 0.080 (0.008) | 0.080 (0.008) |
| $\beta$ | 0.344 (0.005) | 0.344 (0.005) | 0.319 (0.005) | 0.319 (0.005) |
| $\Theta$ | 0.545 (0.005) | 0.545 (0.005) | 0.529 (0.005) | 0.529 (0.005) |
| $\alpha$ | 0.079 (0.003) | 0.079 (0.003) | 0.115 (0.005) | 0.116 (0.005) |
| $\eta$ | 0.007 (0.002) | 0.007 (0.002) | 0.017 (0.004) | 0.016 (0.004) |
| $\tau$ | | | 2.219 (0.106) | 2.249 (0.109) |
| Adjusted $R^2$ | 0.926 | 0.926 | 0.927 | 0.927 |

A: Base regression (does not allow for capital utilization or learning-by-doing effects); physical decay measured by BEA economic depreciation rates.
B: Base regression; no physical decay allowed for.
C: Full specification (adjusts for capital utilization and includes variables capturing learning-by-doing effects associated with investment spikes); physical decay measured by BEA economic depreciation rates.
D: Full specification; no physical decay allowed for.

Next, we entertain the possibility that physical depreciation rates are near-geometric and amount to various fractions of the BEA rates. We construct the parameterized capital stock using as physical depreciation rates some fraction times the BEA-provided rate for each observation's industry and year. We then estimate how $\gamma$ varies. Table 2-3 and Figure 2-3 contain the results. As expected, the lower is the

[31] Deflating by the equipment-investment deflator instead of the PCE deflator does not change our conclusions.

assumed depreciation rate the higher is the estimate of $\gamma$, which ranges from 0 to 25 percent (with a standard error of approximately 6 percent). Clearly as we allow less and less of the decrease in productivity of early vintages of investment over time to be explained by physical decay, $\gamma$ is left to explain, rightly or wrongly, more of this decrease. Total economic depreciation, the sum of physical decay and obsolescence, ranges from 13 to 25 percent. Also shown in Figure 2-3 is the average BEA economic depreciation rate of 12% and the implied rates of obsolescence as the physical depreciation rate is increased. Our estimated $\gamma$'s and implied economic depreciation rates differ from those suggested by the BEA data in two important respects. First, except when physical depreciation is assumed to be 100% of the BEA rates, our $\gamma$'s and economic depreciation rates are substantially higher (though not statistically so). Second, the $\gamma$'s exhibit a steepening rather than constant slope as assumed physical depreciation increases. This suggests that the assumption of near-geometric physical depreciation rates may be inappropriate.

## Table 2-3

## Results with Physical Depreciation as a Fraction of BEA Rates

| Fraction of BEA rates | Estimated $\gamma$ | Implied Economic Depreciation Rate[1] |
|---|---|---|
| 0 | 0.245 (0.065) | 0.245 |
| 0.25 | 0.205 (0.064) | 0.236 |
| 0.5 | 0.159 (0.061) | 0.220 |
| 0.75 | 0.087 (0.053) | 0.178 |
| 1 | 0.005 (0.042) | 0.126 |

Note: All of the estimates in column 2 were obtained using the same, preferred specification: adjustment to control for unobserved utilization and spike dummies included to control for learning-by-doing effects (i.e., the same specification as was used in Table 1, Column C).

*E. Estimates from Cross-sections*

It is impossible to decompose productivity change into its embodied and disembodied components by using time series data for a single plant, firm, industry, or economy (see Hall (1968) for a discussion of this identification problem). The basic insight of this chapter is that, armed with data on physical depreciation, one can isolate the embodied component by exploiting the large cross-sectional variation in investment histories within a given year that is available at the plant-level. In principle, we could estimate our model (equation (2-10)) using only one cross-section. However, we pooled many cross-sections in order to maximize the number of observations (and therefore the variation in investment distributions). Naturally, one may ask whether similar estimates of $\gamma$ may be obtained with the cross-sections alone.

Table 2-4 shows the results of such an exercise using cross-sections from 1980-96 of our primary sample. The top portion of the table involves a specification in which unobserved utilization is controlled for (as in Column C of Table 2-1). It is clear from the large standard errors here that pooling the cross-sections is vital to obtaining any reasonable precision on $\gamma$. The median estimate, mean estimate, and standard error of the mean are 0.239, 0.216, and 0.046, respectively.

## Table 2-4 Results from Cross-Sections

| Gamma | Std. error | Adjusted $R^2$ | Cross-section year | Control for Utilization |
|---|---|---|---|---|
| 0.256 | 0.123 | 0.930 | 96 | Yes |
| 0.253 | 0.114 | 0.895 | 95 | Yes |
| 0.286 | 0.126 | 0.912 | 94 | Yes |
| 0.109 | 0.073 | 0.940 | 93 | Yes |
| 0.239 | 0.112 | 0.937 | 92 | Yes |
| 0.134 | 0.092 | 0.897 | 91 | Yes |
| 0.129 | 0.124 | 0.889 | 90 | Yes |
| 0.091 | 0.098 | 0.891 | 89 | Yes |
| 0.382 | 0.197 | 0.909 | 88 | Yes |
| 0.236 | 0.174 | 0.921 | 87 | Yes |
| -0.118 | 0.117 | 0.887 | 86 | Yes |
| -0.099 | 0.108 | 0.883 | 85 | Yes |
| 0.307 | 0.262 | 0.883 | 84 | Yes |
| 0.877 | 0.399 | 0.930 | 83 | Yes |
| -0.140 | 0.130 | 0.926 | 82 | Yes |
| 0.442 | 0.403 | 0.929 | 81 | Yes |
| 0.282 | 0.290 | 0.893 | 80 | Yes |
| | | | | |
| 0.172 | 0.075 | 0.929 | 96 | No |
| 0.203 | 0.078 | 0.894 | 95 | No |
| 0.164 | 0.076 | 0.911 | 94 | No |
| 0.048 | 0.045 | 0.939 | 93 | No |
| 0.079 | 0.055 | 0.936 | 92 | No |
| 0.069 | 0.060 | 0.896 | 91 | No |
| 0.062 | 0.071 | 0.888 | 90 | No |
| 0.077 | 0.078 | 0.890 | 89 | No |
| 0.198 | 0.116 | 0.908 | 88 | No |
| 0.119 | 0.106 | 0.920 | 87 | No |
| -0.081 | 0.092 | 0.886 | 86 | No |
| -0.072 | 0.086 | 0.882 | 85 | No |
| 0.183 | 0.167 | 0.883 | 84 | No |
| 0.171 | 0.134 | 0.929 | 83 | No |
| -0.109 | 0.105 | 0.926 | 82 | No |
| 0.141 | 0.197 | 0.928 | 81 | No |
| 0.255 | 0.246 | 0.893 | 80 | No |

Note: The same regression is run, either with or without allowing for capital utilization, for each cross-section year between 1980 to 1996. As with the pooled regressions, for any cross-section investment is observed from a plant's birth until the current cross-section year. In all regressions, industry dummies are included.

Despite the large standard errors, one may wonder if the large variation in $\gamma$ across cross-sections indicates that the true $\gamma$ has varied greatly over time. To test this, we estimate our full specification on the pooled sample allowing $\gamma$ to vary by year and test the hypothesis that $\gamma$ is constant. The F-statistic for this test is 0.17 compared to a 95% critical value of 1.00. Thus, one cannot reject the hypothesis of a constant $\gamma$ over cross-sectional years.

The cross-sectional results in Table 2-4 are also helpful in assessing whether our pooled estimate of $\gamma$ is affected by the assumption that the elasticity of energy usage with respect to capital utilization, $\tau$, is constant. It is possible that $\tau$ was lower in the 1970's when energy costs were high than it was in the 1980's and 1990's. It can easily be shown that the contribution of equipment capital to output, $\alpha(\tau\text{-}1)/\tau$, is increasing in $\tau$. If the constant average, and estimated, $\tau$ is higher (lower) than the true $\tau$ for early (later) vintages, then the contribution of early vintage equipment to output would be overstated (understated). To compensate, the estimation procedure in its efforts to minimize the sum of squared errors will want to underweight early vintage investment relative to later investment as it searches for the SSE-minimizing $\hat{\gamma}$. This implies an upward bias in $\hat{\gamma}$. This is a possible explanation for the increase from 8% to 17% when we adjust for utilization (see Columns A and B of Table 2-1).

However, our cross-sectional results provide strong evidence that this is not the case. In the cross-sections, $\tau$, like all other parameters, is estimated separately for each year. The bottom portion of Table 2-4 refers to the specification that does not control for unobserved capital utilization (same as in Column A of Table 2-1). If the 9% difference we get in the pooled regressions is due to an unaccounted-for trend in $\tau$, then this difference should disappear in the cross sections. In fact, on average, this difference is slightly higher (though not significantly so) at about 10% for any particular cross-section.

Furthermore, allowing only $\tau$ to vary by year and estimating our full specification over the pooled sample yields a gamma of 0.127 (0.054) compared to the 0.116 (0.060) in Table 2-1, Column C. $\tau_t$ does in fact exhibit a slight rising trend over time which is statistically significant according to a Wald test.[36]

*F. Results from other Samples*

As mentioned in Section 5, our primary sample, POST72A, was chosen so as to minimize the possible effect of several biases. We now present results using other samples.[37] POST72B was created in order to evaluate the likelihood of a “survivorship” bias. There is a possible sample selection bias introduced by the fact that unproductive plants are unlikely to survive for many consecutive years and our primary sample excludes plants that have not survived for at least 4 years.[38] Plants with high expected present discounted values of future profits may be more likely to invest in high-tech equipment than plants with less rosy prospects for the future. These plants are also more likely to survive for a long period. Moreover, investing in high levels of embodied technology is likely to be a cause of future profitability and survival[39].

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[32] The F-statistic for the test of the null hypothesis that $\tau$ is constant for all years is $8.48 > F_{J,T-K}(.95)=1.00$.

[33] Section 5 describes the various samples and discusses the potential biases that are involved.

[34] Evidence that less productive plants are less likely to survive than more productive plants may be found in Baily, Hulten, and Campbell (1992), and Olley & Pakes (1996), among others.

[35] This intuition is confirmed in a study by Timothy Dunne (1991) who analyzes plant-level data from the Survey of Manufacturing Technology. He shows that large, old

Therefore, plants with higher than average shares of vintage investment in high-tech equipment in the early years of the sample are more likely to be included in POST72A. Having higher than average (relative to the average manufacturing plant in a given year) levels of embodied technology in the early years of the sample should result in a *downward* bias in $\gamma$. However, our results show that $\hat{\gamma}$ is actually higher (though not significantly so) with our primary sample compared to that with POST72B, which seems to indicate that this potential source of bias is not a serious concern. This can be seen in Table 2-5 which displays the results from estimating our full specification using each of our four samples.[40]

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plants utilize new technologies more intensively than young, small plants.

[36] For estimations using the POST72B sample, we include a dummy variable indicating whether or not the plant was born in the previous year together with two lags of this. The coefficients on these variables indicate that all else equal, productivity is 2.5% below average in the first year after a plant's birth, 2.1% below two years after, and 1.7% below three years after.

## Table 2-5 Results from Alternative Samples

| | Sample | | | |
|---|---|---|---|---|
| Parameter | POST72A | POST72B | SCREEN | 72-96 PANEL |
| $\gamma$ | 0.116 (0.060) | 0.085 (0.069) | 0.209 (0.034) | 0.039 (0.042) |
| Intercept | 2.369 (0.080) | 2.441 (0.085) | 2.324 (0.047) | 2.244 (0.080) |
| Multi | 0.080 (0.008) | 0.098 (0.006) | 0.059 (0.005) | 0.083 (0.012) |
| $\beta$ | 0.319 (0.005) | 0.354 (0.004) | 0.324 (0.001) | 0.299 (0.005) |
| $\Theta$ | 0.529 (0.005) | 0.496 (0.004) | 0.545 (0.003) | 0.566 (0.005) |
| $\alpha$ | 0.114 (0.005) | 0.112 (0.004) | 0.099 (0.002) | 0.088 (0.004) |
| $\eta$ | 0.018 (0.004) | 0.019 (0.004) | 0.025 (0.001) | 0.028 (0.003) |
| $\tau$ | 2.219 (0.105) | 1.909 (0.055) | 2.731 (0.092) | 6.569 (1.397) |
| Adjusted $R^2$ | 0.927 | 0.934 | 0.925 | 0.903 |
| N | 96846 | 163191 | 224337 | 184678 |

Note: All 4 columns refers to the full specification (i.e. that in Table 1, Column C). The "POST72B" regression also includes three dummy variables indicating whether the plant was born one year ago, two years ago, or three years ago.

The SCREEN sample is an effort to increase the sample size and representativeness by including observations from plants which have a small amount (less than 20% of current equipment assets) of unobserved pre-1972 investment. However, because pre-1972 investment is omitted and no variable is available to proxy for it, this introduces an omitted variable bias, the direction of which depends on the correlation between pre-1972 and post-1972 equipment investment. In a model of lumpy investment, the larger a plant's current effective capital stock, the less likely the plant is to invest in new capital, implying a negative correlation.[41] This implies a

[37] This intuition is supported by Cooper, Haltiwanger, and Power (1999) who find that the probability of investment in a given year increases with the time since the plant's

negative bias on $\alpha$. Evaluating the likely bias on $\gamma$ is more complicated. The correlation between pre- and post-1972 investment should be more negative for early post-1972 investment since as time goes on the pre-1972 equipment is gradually retired and therefore no longer contributes to production (and hence does not factor into contemporaneous investment decisions). Thus, the omitted pre-1972 equipment causes one to underestimate the contribution of early vintages relative to later vintages. This implies a positive bias on $\gamma$.

These priors are in fact supported by the data. The estimate of $\alpha$ falls from 0.114 with POST72A to 0.099 with SCREEN, while $\hat{\gamma}$ rises from 0.116 to 0.209.

Finally, because balanced panels are commonly used in plant-level studies, we also created a sample consisting only of plants that were continuously observed from 1972 to 1996. This sample is also affected by the omission of pre-1972 investment and is likely to be strongly affected by a survivorship bias as well. Though we found no evidence of a survivorship bias in our primary sample where plants could not exit until after 4 years, a survivorship bias seems far more likely in this balanced panel of 25 years. The $\hat{\gamma}$ obtained using this sample is 0.039. Though it is possible that large, old, and successful plants have a lower *true* rate of embodied technological change, it seems more plausible that this lower $\hat{\gamma}$ is evidence of a serious survivorship bias.

*G. Simultaneity Bias*

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last large investment.

It is well known that OLS estimation of production function relationships is subject to potential simultaneity biases.[42] Since the "independent" variables are production inputs that are chosen optimally by the producers, the usual exogeneity assumptions that are required for the consistency of OLS may fail. A plant manager's input choices are determined by plant quality (or, equivalently, managerial efficiency or disembodied technology) along with factor prices and product demand. Since part of this quality is unobserved by the econometrician, it is subsumed into the disturbance term of the production function. The result is that variable inputs may be correlated with the disturbance term.

To address the possibility of simultaneity bias, we attempted a non-linear instrumental variables (NLIV) estimation. An appropriate set of instrumental variables should include all exogenous variables in the model together with other exogenous and relevant (i.e. correlated with the Jacobian vector of first derivatives of the model with respect to the parameter vector) instruments. For identification it is necessary to have at least one instrument per parameter to be estimated. Unfortunately, it is very difficult to find good instruments (exogenous and relevant) at the plant level for our purposes. This limits severely the success of our NLIV estimations as we will see below. In order to address these problems partially, we try to minimize the number of parameters to be estimated by following a suggestion of Griliches and Ringstad (1971). We replace factor elasticities of some or all of the inputs (e.g. of materials and labor) with measures of their share in cost (using 4-digit industry-level data from the NBER-CES

[38] Marschak and Andrews (1944) were the first to recognize this problem. Griliches and Mairesse (1995) provide a thorough discussion of the issue together with attempts to ameliorate the problem using plant-level data.

Productivity Database and 2-digit equipment and structures rental rates from the BLS).

For instruments, we use the set of 4-digit industry-level downstream demand indicators originally constructed by Bartelsman, Caballero, and Lyons (1994) and modified by Baily, Bartelsman, and Haltiwanger (1996). An industry's demand indicator is a weighted average of the economic activity of manufacturing and service industries (downstream industries) that purchase the industry's output. The weights are the share of each downstream industry's purchases in the upstream industry's total output and the measure of economic activity is the sum of the cost-share weighted growth rates of each factor input (capital, labor, and materials). In order to filter out any endogenous effect that an upstream industry's productivity may have, through its output price, on downstream industries' activity, the indicator excludes the activity of downstream industries whose purchases from the upstream industry are greater than 5% of their total intermediate input purchases. The instrument set also includes the second through fourth powers of this downstream demand indicator, and investment lagged 3 through 24 years (24 is oldest possible non-zero lagged investment that a plant in our sample can possibly have).[43]

The results of these regressions are shown in table 2-6. Column A shows the regression results from our preferred specification where labor's and material's elasticities are not estimated but rather are measured by their industry cost shares. Column B shows the results from the same regression except that all factor elasticities

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[39] It may be argued that past investment, even lagged more than three years, is endogenous. Unfortunately, when we omit lagged investment from our set of instruments, our first-stage $R^2$ drops substantially and the standard errors rise making the estimates essentially meaningless.

are measured by their industry cost shares and no utilization adjustment is made.[44] Column C contains results from an average vintage specification also without a utilization adjustment and with all factor elasticities measured by cost shares.

## Table 2-6 Results from NLIV Estimation

| | A | B | C |
|---|---|---|---|
| $\gamma$ | 0.332 (0.319) | -0.134 (0.048) | 0.144 (0.098) |
| Intercept | -0.030 (0.980) | 1.519 (0.029) | 2.494 (1.006) |
| $\alpha$ | 0.166 (0.033) | | |
| $\eta$ | 0.112 (0.030) | | |
| Multi | -0.269 (0.047) | 0.058 (0.011) | 0.049 (0.010) |
| Scale | | 0.939 (0.007) | 0.947 (0.006) |
| P-value for Test of over-identifying restrictions | 1.000 | 1.000 | 1.000 |
| Adjusted $R^2$ | 0.905 | 0.905 | 0.906 |

A: Regression with labor and materials elasticities measured by industry cost-shares.
B: Regression with all factor elasticities measured by industry cost-shares.
C: Average vintage regression with all factor elasticities measured by industry-level cost-shares.
Note: Regressions A-C also include year and industry dummy variables.

The results of our IV estimations are inconclusive. Largely due to the inclusion of lagged investment in our instrument set, our first-stage $R^2$'s (not shown) are fairly high, particularly for the first derivative of $\gamma$. Yet, despite this apparent relevance, we are not able to estimate $\gamma$ with any reasonable degree of precision. Of the three

[40] The iterative estimation procedure was not able to converge when $\tau$ was included in the regression.

regressions shown, only the estimate of $\gamma$ in column B is significant. Based on unreported OLS results we conclude that the negativity of $\hat{\gamma}$ is most likely due to the imposition of the industry cost-shares rather than to the use of IV. In summary, despite our efforts to instrument for endogeneity, we are not able to rule out the possibility of simultaneity bias in our estimate of $\gamma$.

The recent literature on nonconvexities in investment behavior, however, provide one argument for why endogeneity may not be a problem here. As stated above, the simultaneity bias results from a positive contemporaneous correlation between investment and productivity shocks (the disturbance in our regressions) combined with serial correlation of productivity shocks (resulting in a correlation between past investment and current productivity shocks). The contemporaneous response of investment to a productivity or profitability shock will depend upon the adjustment cost function and the size of the shock. Nonconvexities, particularly of an (S,S)-nature, imply a small response or no response at all for relatively modest shocks. If most of the mass of the distribution of shocks is in the inaction-range (i.e. inside the S,S bands), then endogeneity should be a minor problem. Cooper & Haltiwanger (2000), in fact, use an LRD dataset similar to ours and find that the adjustment cost function is U-shaped with very little response in investment to small profit shocks. Unfortunately, the true productivity shocks in our sample are not observed of course, so we cannot plot this distribution to confirm that most of its mass is in the inaction range.

*H. Why do I not use the Olley and Pakes (1996) method?*

Olley and Pakes (1996) present a model of plant behavior that motivates a three-stage algorithm for estimating a production function while controlling for factor endogeneity and selection bias due to endogenous exit. The model relies crucially on an “invertibility condition.” This amounts to investment being a monotonic function of unobserved productivity, and observed plant state variables such as capital stock. This allows productivity to be expressed as an inverse function of investment and these state variables.

In the first two stages of the Olley-Pakes algorithm, output is projected on the variable inputs and a polynomial function, which proxies for unobserved productivity, in terms of investment and the plant-specific state variables (capital and age in their model). The probability of survival is then estimated as a similar polynomial. In the third and final stage, the estimated values of the contribution to production from variable factors and productivity, and the endogenous effects of survival, from the first two stages, are subtracted from output and the remainder is regressed on the plant-specific state variables in order to estimate their contributions to production. For our study, the second stage of their method would not be necessary since our data sample allows for most entry and exit and thus largely eliminates the possibility of selection bias from only observing plants that survive for the length of the panel.

Why not then apply the Olley-Pakes approach to our model which allows for the embodied technological change? The problem is that capital stock is not an observed plant state variable in our approach. We use a parameterized stream of current and past investment rather than a capital stock construct. This renders unidentifiable the separate effects of embodied technology in current investment and the productivity signal of current investment.

## 7. Productivity Growth Decomposition

Our findings have the important implication that the equipment capital stock is mismeasured considerably in studies of productivity growth or production function estimation. In particular, we estimate that the stock of equipment grows at much faster rates than is reflected in conventional methods. As may be seen in Table 2-7, the growth rate of equipment capital stocks depends crucially on the assumptions made on physical depreciation, the investment-price deflator, and the rate of growth of embodied technological change.[45] We calculate the annual growth rate of equipment capital stock under five different sets of assumptions.[46] The growth rate of the stock implied by the results from our main regression (Column C of Table 2-1), with $\gamma$=0.116, is 14.7 percent. This is substantially higher than the growth rate of the conventional capital stock ($\gamma$=0, investment deflated by the FRB/PPI investment deflators and adjusted for depreciation using the BEA/Hulten-Wykoff rates), which is 4.2 percent in our sample. It is also far above the growth rates of the capital stocks

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[41] For the construction of these capital stocks, a numeraire year ($t_0$) of 1972 was used. The choice of numeraire year *can* affect whether the growth rate of capital is monotonically increasing or monotonically decreasing in $\gamma$. This can be seen easily by taking the derivative of ($J_t/J_{t-1}$) with respect to gamma where $J_t$ is defined according to equation (2-14). Choosing a numeraire year at the beginning of our sample ensures that the growth rate will increase with $\gamma$. What is important for comparing capital stock growth rates using different $\gamma$'s is not necessarily the sign of this derivative, but just that the derivative is monotonic in $\gamma$.

[42] Specifically, we regress the log of equipment capital stock on t and an intercept. The coefficient on year gives the average annual growth rate.

endorsed by either Hulten (1992) or Greenwood, et al. (1997), which are both 7.0 percent in our sample. The key element that generates the higher growth rate in our capital stock construct is the value of $\gamma$. When we set $\gamma$ to zero but use the FRB/BLS depreciation data and the PCE deflator to construct the capital stock its growth rate is only 4.4 percent.

## Table 2-7

## Annual Growth Rates in Equipment Capital from 1972-96

| Type of Equipment Capital Stock | Our Sample | Aggregate Manufacturing |
|---|---|---|
| A. This paper -- $\gamma$ = 11.6% | 14.7% | 14.0% |
| B. This paper -- $\gamma$ = 7.7% | 11.2% | 10.0% |
| C. This paper -- $\gamma$ = 0 | 4.4% | 2.1% |
| D. Conventional | 4.2% | 3.0% |
| E. Hulten (1992) | 7.0% | 6.0% |
| F. Greenwood, et al. (1997) | 7.0% | 5.7% |

A -- The equipment capital stock implied by the $\gamma$ found in Table 1, Column C: $\gamma$=0.116 and the FRB physical depreciation schedules and the PCE deflator are used.
B -- $\gamma$ = 0.077, FRB physical depreciation, and PCE deflator.
C -- $\gamma$ = 0, FRB physical depreciation, and PCE deflator.
D -- $\gamma$ = 0, BEA depreciation, and FRB/PPI investment deflators.
E -- $\gamma$ = 0.03, BEA depreciation, and FRB/PPI investment deflators.
F -- $\gamma$ = 0.03, BEA depreciation, and deflator for PCE of nondurables and nonhousing services.

We now examine the relative importance of embodied and disembodied technological change for productivity growth in our sample of U.S. manufacturing plants. According to equation (2-3), the residual growth rate in output, after accounting for quality-adjusted input growth, is due to technological change that is not embodied in equipment investment. That growth rate in our sample is 0.57 percent annually.[47] Correspondingly, the rate of output growth that is due to embodied technological change is equal to the equipment elasticity times the differential growth rate of quality-adjusted and non-quality adjusted equipment capital stocks. This measure averages 1.17 percent annually in our sample.[48] The implication is that equipment-embodied technological change accounted for about two-thirds of total technological change between 1972 and 1996 in our sample of U.S. manufacturing plants.

## 8. Conclusion

Determining the rate of embodied technological change is of crucial importance. It is a necessary ingredient for productivity analysis which relies on accurate measures of capital accumulation. Furthermore, it tells us how much of the decline in an asset's value as it ages can be attributed to obsolescence.

In this chapter, we developed a production-side approach that can provide alternative estimates of embodied technological change to price-based estimates. We found that the rate of embodied technological change for the typical manufacturing plant is between 8 and 17 percent. These rates are much higher than that suggested by the relative rate of decline of Gordon's (1990) equipment price deflators which puts it no higher than 4%. These results are consistent with arguments made by Hornstein and

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[43] This number comes from the coefficient on t after regressing the log of TFP, constructed using the equipment capital stock with a $\gamma$=.116, on t and an intercept.

[44] The equipment elasticity is 0.114 from Column C of Table 2-1. The approximate annual growth rate in the equipment capital stock due to embodied technological change is 10.3 percent. This number comes from subtracting the 14.7 percent in Row A of Table 2-7 from the 4.4 percent in Row C.

Krusell (1996), Gort and Wall (1998), and others who argue that these price-based estimates are likely to understate true embodied technological change.

If our estimates are accurate, embodied technological change may account for as much as two-thirds of the total growth in TFP, suggesting an important role for investment in spuring productivity growth above and beyond its traditional role of capital deepening.

Chapter 3

**Measuring Embodied Technological Change via Upstream Research and Development**

## 1. Introduction

Chapter 2 proposed an production-side approach to measuring embodied technological change that exploits time-series and cross-sectional variation in investment histories. Inter alia, the current chapter extends this approach to allow the estimates of embodied technological change to vary by industry. Nonetheless, there remain two inherent limitations of these estimates: (1) they can only be obtained for manufacturing industries, and (2) there are no comparable results in the literature with which to evaluate the reasonableness of these estimates. That is, how does one know whether it is sensible for one particular industry to have a higher estimated rate of embodied technological change than another. An inspection of capital flows tables may be able to tell us which industries invest in goods that are considered "high-tech," but other than subjective priors, we have no way of quantifying how high-tech an industry's capital goods are.

In order to evaluate the realism of estimated rates of embodied technological change in manufacturing industries and to extend these results to non-manufacturing industries, I first attempt to estimate the relationship between an industry's estimated rates and it's distribution of capital across asset types. This estimation fails to provide a sufficiently high degree of precision to be useful for imputing non-manufacturing rates of embodied technological change. Next, I propose two alternative indices that are meant to capture the amount of research and development (R&D) embodied in an industry's capital and then investigate the effectiveness of each index in explaining embodied technological change. Each index is a weighted average of past and present R&D performed on the (upstream) capital goods purchased by a (downstream) industry. To construct these indices, I create a data set containing R&D by product field from 1957 to 1997, using various releases of the National Science Foundation's *Research and Development in Industry*. This data is then combined with Commerce Department data on industry investment by asset type. The *product field* R&D data allows me to avoid measurement problems associated with using R&D by *performing industry*.

After discussing many of the interesting features of the constructed indices, I search for some reduced-form relationships between embodied R&D and either the estimated rates of embodied technological change that I find at the plant-level or the Solow Residual.[49] It turns out that the *level*, but not the *growth rate*, of embodied R&D is positively and significantly related to both the Solow Residual and the estimates of embodied technological change. This mirrors the relationship I find between the product-oriented R&D applied to equipment assets and the rates of technological change in these assets implied by their relative price movements.

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[1] There is a large literature seeking to measure the effects of R&D on productivity. However, the R&D variable that is generally used is R&D done *by* the firm, industry, or economy for which productivity is being measured. There is also a growing literature on the productivity effects of R&D spillovers -- that is, R&D done by other firms that are "close" to the firm/industry in question in terms of distance, industry, production process, input-output linkages, etc.. Though interesting in their own right, these types of R&D effects are likely to affect disembodied technological change and thus are separate from the embodied effects of R&D discussed in this paper.

## 2. Industry-Specific Estimates of Embodied Technological Change

Using the same sample and model as that used for the regression in Table 2-1, Column C, but interacting $\gamma$ with an industry dummy variable, I am able to estimate $\gamma$ separately for each sector/industry. The estimates of $\gamma$ by sector are shown in the third column of Table 3-1. The estimates seem sensible for the most part with the exception of some slightly negative estimates and unrealistically high values in Computers (16) and Electronic Components (19). The negative values are not too disturbing given their rather high standard errors. They also occur in sectors where one might expect low levels of embodied technology. It seems reasonable to interpret these negatives as findings of $\gamma=0$ for these sectors and thus I replace the negative $\gamma$'s with zero for constructing quality-adjusted capital stocks. The very high $\gamma$'s in sectors 16 and 19 are most likely a result of the use of the BEA's 4-digit level shipments deflators. These deflators come from the BLS with two key exceptions: computers and semiconductors (semiconductors are a component of sector 19). I have also tried estimating the model using the personal consumption expenditures (PCE) deflator (which has some theoretical justification as discussed in Section 2 of Chapter 2). The results are shown in the fourth column of Table 3-1. Using the PCE deflator for output results in a strongly negative $\gamma$ for the Computer industry and zero for the Electronic components industry, results which are clearly unrealistic as are many of the other obtained estimates. Therefore, throughout this chapter I use the $\gamma$'s in the third column of Table

3-1, with the caveat that the relative rank of $\gamma$ may be more informative than the actual levels.[50]

**Table 3-1 Industry-Level Estimates of Embodied Technological Change in Manufacturing**

| Sector | Sector Title | SIC (1987 basis) | $\hat{\gamma}$ ($P_{nber}$ used) | $\hat{\gamma}$ ($P_{pce}$ used) |
|---|---|---|---|---|
| 1 | Food & Tobacco | 20 and 21 | -0.056 (0.021) | -0.138 (0.018) |
| 2 | Textiles and knitting | 22 | 0.098 (0.030) | -0.048 (0.026) |
| 3 | Apparel | 23 | 0.004 (0.025) | -0.063 (0.022) |
| 4 | Paper | 26 | -0.064 (0.027) | 0.050 (0.028) |
| 5 | Printing & publishing | 27 | -0.053 (0.023) | 0.148 (0.027) |
| 6 | Chemicals | 28 | -0.004 (0.024) | 0.059 (0.024) |
| 7 | Petroleum refining & Fuel Oil | 29 | 0.017 (0.039) | -0.050 (0.035) |
| 8 | Rubber & Plastic products | 30 | 0.084 (0.026) | -0.031 (0.022) |
| 9 | Shoes & leather | 31 | -0.046 (0.052) | 0.042 (0.054) |
| 10 | Lumber | 24 | 0.007 (0.023) | 0.113 (0.024) |
| 11 | Furniture | 25 | -0.056 (0.028) | -0.138 (0.029) |
| 12 | Stone, clay & glass | 32 | 0.006 (0.026) | 0.056 (0.025) |
| 13 | Primary metals | 33, 3462, 3463 | 0.080 (0.029) | 0.054 (0.027) |
| 14 | Metal products | 34, exc. 3462,3463 | -0.005 (0.022) | -0.008 (0.021) |
| 15 | Industrial Equipment, except computers & office eqp. | 35, exc SIC's in sector 16 | 0.031 (0.024) | 0.119 (0.024) |
| 16 | Computers & other office equipment | 3571,3572,3575,3577, 3578, 3579 | 2.927 (0.202) | -0.220 (0.031) |
| 17 | Electrical eqp. except communications and elec. components | 36, exc. 366, 367 | 0.049 (0.029) | 0.020 (0.027) |
| 18 | Communication equipment | 366 | 0.141 (0.044) | -0.044 (0.036) |
| 19 | Electronic components | 367 | 0.766 (0.059) | 0.008 (0.031) |
| 20 | Motor vehicles & parts | 371 | -0.064 (0.028) | -0.004 (0.028) |
| 21 | Other transportation equipment | 37, exc. 371 | 0.098 (0.033) | -0.048 (0.034) |
| 22 | Scientific Instruments | 38, exc. 384, 385 | -0.023 (0.034) | -0.089 (0.031) |
| 23 | Other instruments | 384, 385, 382, 386, 387 | 0.087 (0.039) | 0.122 (0.039) |
| 24 | Miscellaneous manufacturing | 39 | 0.029 (0.032) | 0.058 (0.031) |

## 3. The Relationship Between $\hat{\gamma}$ and Investment Asset Shares

[2] Correspondingly, rank (Spearman's) correlations will be provided in addition to the ordinary (Pearson's) correlations.

In order to impute nonmanufacturing $\gamma$'s as well as to evaluate the sensibility of their rank across industries, it would be nice if there were observable variables that vary by industry and which are likely to be proportional to the true rates of embodied technological change. Since $\gamma$ can be thought of as a weighted average of the rates of embodied technological change for each particular capital asset, the asset mix of an industry (from the BEA's Fixed Reproducible Tangible Wealth data) is one possibility. However, given only 24 sectors, these asset shares had to be combined into a small number ($n<24$ is required for identification if $\gamma$ is regressed on asset shares). Ideally, we would like to aggregate them into a small number of groups that differ according to the levels of technology. Thus, the disadvantage of using asset shares is that the process of aggregation requires some arbitrary decisions on what assets are considered "high-tech" vs. "low-tech."

The NIPA uses an equipment asset breakdown consisting of 4 categories: 1) "Information processing and related equipment," 2) "Industrial equipment," 3) "Transportation and related equipment," and 4) "Other equipment" (see Table 5.8 - NIPA). Using this classification scheme, I aggregate the FRTW's data on industries' investment in each of 35 equipment assets to investment by NIPA category. For each industry, the share of total investment in each of the four asset categories is calculated and averaged from 1972-96.

Our estimates of $\gamma$ were then regressed on the four 1972-96 average asset shares.[51] The results of this regression are shown in Table 3-2. The first column

[3] These shares sum to 1, therefore a constant cannot be included in this regression in order to maintain full rank in the regressor matrix.

contains the $R^2$ and coefficient estimates from performing OLS regression. The second contains the results from a quadratic programming algorithm which finds the coefficients on the asset shares which minimize the sum of squared errors while constraining each coefficient to be greater than zero. This was done in order to ensure that imputed $\gamma$'s for nonmanufacturing would be positive (negative $\gamma$'s are unrealistic). The estimated coefficients in the unrestricted case are very imprecise and 3 of the 4 are negative. The only sensible result of this regression is that the coefficient on "Information processing" is, as one would expect, is positive (though the standard error is quite large). The linear programming coefficients seem more realistic, however they are extremely imprecise. Thus, it appears that a relationship between asset shares and $\gamma$ cannot be estimated with a sufficiently high degree of precision to be useful for imputing rates of embodied technological change in nonmanufacturing.

**Table 3-2 Regression of $\hat{\gamma}$ on Investment Asset Shares**

| | Coefficients unbounded | Coefficients bounded to be > 0 |
|---|---|---|
| Info. Processing | 1.818 (0.947) | 0.058 (1.027) |
| Industrial Equipment | -2.043 (1.225) | 0.168 (1.329) |
| Transportation and related | -1.396 (3.476) | 0.019 (3.770) |
| Other Equipment | -3.215 (3.126) | 0.000 (3.391) |
| $R^2$ | 0.135 | -0.018 |

## 4. Embodied R&D as a Proxy for Embodied Technology

A natural choice for a variable that is likely to be related to $\gamma$ would be the amount of research and development (R&D) that went into developing the technology that is embodied in an industry's capital. As Hulten (1996) puts it: "Most advances in knowledge are the result of systematic investments in research and development." So if R&D is how technology is produced (I provide evidence of this in Section 6), then R&D directed towards the equipment assets used by an industry is the main input into the "production" of its capital-embodied technology. To capture this notion of "capital-embodied R&D," I create two alternative indices which are weighted averages of past and present R&D done on an industry's equipment capital. As opposed to inferring embodied technology from an industry's asset composition, embodied R&D has the advantage of being a single metric which reflects both the changing asset mix of an industry's capital *and* the technological advances (to the extent they are due to R&D) that have taken place in each asset type. The hope is that these indices will be useful predictors of either the level or the change in embodied technology. We can define the level of embodied technology for investment of vintage t-s in terms of equation (2-14) as:

$$q_{t-s} = (1+\gamma)^{t-s-t_0} \tag{3-1}$$

Note that from equation (2-14) it is clear that q refers to the level of embodied technology *per unit* of investment.[52]

The indices I construct in this paper are related yet very different from the

[4] As discussed in Chapter 2, the proper unit of measurement for $I_{t-s}$ is nominal investment deflated by the PCE deflator.

typical measures of embodied or "indirect" R&D in capital that are used in the literature on R&D spillovers. The literature on indirect/embodied R&D is concerned with measuring the extent to which upstream R&D affects the productivity of downstream industries. Clearly, *process*-oriented R&D should exclusively benefit the industry(ies) who utilize the R&D-induced process innovations and should have no effect on either the measured or real productivity of those industries who purchase the R&D performer's product.

However, the effects of *product*-oriented R&D (which is the majority of R&D) are more complex. As pointed out by Scherer (1982) and Griliches (1979), much of measured downstream benefits of R&D may be due to measurement error in the price of capital goods. If prices adjusted fully for quality change, real output for capital producers and real investment for downstream industries would be augmented to reflect the increased quality embodied in the capital being produced. One would then expect to observe the majority of productivity gains (if there were any) in the capital-supplying industry and smaller gains in the downstream industries. The downstream gains that do occur, known as *pure* rent spillovers, are the result of price competition in the upstream industry which prevent the nominal price of newly-invented capital from increasing in proportion to the increase in quality. On the other hand, if prices do not adjust for quality, then real output of the supplying industry and real investment of purchasing industries will be understated. In this case, increases in measured productivity should show up primarily in the downstream industries. Whether the downstream measured productivity gains are due to mismeasured capital prices or to pure rent spillovers, either way these gains reflect investment-specific technological change since they would cease to appear if the downstream industry did not invest.[53]

For the purposes of comparison and to avoid confusion with more traditional measures of embodied R&D, it will be helpful to see the measure of indirect R&D in capital generally used in the R&D spillover literature:

$$IRD_i(t) = \sum_j B_{ji}(t) \cdot \frac{RD_j(t)}{Y_j} \qquad (3\text{-}2)$$

where $B_{ji}$ is industry j's sales of capital to industry i, $RD_j$ is the R&D stock for industry j, and $Y_j$ is industry j's output. The R&D stock is generally measured using a perpetual inventory accumulation of past and present R&D expenditures assuming some rate of depreciation. RD/Y is referred to as "R&D intensity." Thus, investment in each upstream industry's product is multiplied by the R&D intensity of that industry and then summed across industries. This measure was developed by Terleckyj (1974) and has been used in numerous studies.[54]

A problem with the Terleckyj approach is that R&D spending (and therefore R&D stock) by an industry is not necessarily equal to the total R&D done on that industry's products. The use of own-R&D is inappropriate if there are non-zero off-diagonal elements in the interindustry R&D flows matrix -- i.e., if industries

[5] Yet another avenue through which upstream R&D could cause downstream investment-specific technological change is knowledge spillovers, i.e. technological diffusion from supplier to customer facilitated by their business interactions.

[6] See, e.g., Scherer (1982, 1984); Goto and Suzuki (1989); Los and Verspagen (2000); Sveikauskas (2000); and Sakurai, Papaconstantinou, and Ioannidis (1997).

perform R&D on products other than their own. There are two reasons to expect this to be a problem. As Griliches and Lichtenberg (1984) point out:

> (1) Many of the major R&D performers are conglomerates or reasonably widely diversified firms. Thus, the R&D reported by them is not necessarily "done" in the industry they are attributed to. (2) Many firms perform R&D directed at processes and products used in other industries. There is a significant difference between the industrial locus of a particular R&D activity, its "origin," and the ultimate place of use of the results of such activity, the locus of its productivity effects. (p.466)

Evidence of this can be seen in the NSF's annual tables on applied R&D by industry and by product field which show numerous large off-diagonal elements in any given year. Thus, a key innovation of this paper is the use of product-field R&D rather than industry own-R&D when measuring embodied R&D.

Surprisingly, though the data is readily available, the NSF data on R&D by product field has rarely been used in economic studies. When it has been used, for example in Griliches and Lichtenberg's study, the productivity effects of product field R&D are sought within the industry which produces that product rather than in downstream industries.

For the purposes of predicting either q or $\gamma$, the Terleckyj measure is inappropriate because it uses investment flows ($B_{ji}$) rather than investment shares (i.e. $B_{ji}$ divided by total investment of industry i). That is, q is the level of embodied technology per unit of investment and therefore should be independent of the scale of an industry's investment (as should its growth rate). Thus, in the indices described below, I use investment shares rather than investment flows.

The first index I construct is based on the premise that an industry's q in a given year is simply a weighted average of the level's of embodied technology in each of the capital goods the industry purchases.  So, let us define the first index, denoted $\Phi^1$, as:

$$\Phi_i^1(t) = \sum_{p=1}^{13} x_{pi}(t) \cdot q_p(t) \qquad (3\text{-}3)$$

where $x_{pi}$ is the share of industry i's equipment investment spent on capital good p, and $q_p$ is the level of technology embodied in capital of asset category (product field) p. We can proxy for $q_p$ with a perpetual inventory accumulation of past and present R&D done on that product field (assuming some depreciation rate), normalized to be 1 in the base year of the prices used to deflate nominal investment:

$$q_p(t) = [(1-d)q_p(t-1) + r_p(t)] / q_p(t_{Base}) \qquad (3\text{-}4)$$

where d is the assumed rate of depreciation and $r_p$ is the R&D spending on product field p, deflated by the PCE deflator.  Given that the real marginal product must be equal across all types of equipment (a necessary condition for the existence of an equipment capital stock) and the fact that real units are identical to nominal units in the base year, $q_p$ must be equal across p in the base year.

It is possible that the productivity of a new capital good depends on the composition of capital in place in a firm or industry.  Under this hypothesis, past changes in asset mix should affect an industry's current level of embodied technology. An index which allows for this possibility is defined by the following equations:

$$\Phi_i^2(t) = (1-d)\Phi_i^2(t-1) + r_i(t) \text{, where}$$

$$r_i(t) = \sum_{p=1}^{13} x_{pi}(t) \cdot r_p(t) \qquad (3\text{-}5)$$

Here a weighted average of current R&D spending on capital goods is fed into a perpetual inventory accumulation. So past R&D as well as past changes in the composition of an industry's capital determine the current level of $\Phi^2$.

An interesting issue is whether $\Phi_i^2$ should be a predictor of $q_i$, the *level* of embodied technology, or for $\gamma_i$, the *growth rate* of embodied technology. Perhaps the composition of capital in place affects not how productive the current vintage of investment is (relative to the base year), but rather how much more productive the current vintage is than last year's vintage. This is left as an open question; in sections 6 and 7, both the level and the growth of $\Phi_i^2$ will be compared to the Solow Residual and the estimated rates of $\gamma_i$.

## 5. Data

The principal source for industrial R&D data in the U.S. is the Survey of Industrial Research and Development, a survey of companies done by the Census Bureau and financed by the NSF. This survey has been done on an irregular basis between 1957 and 1997.[55] Among other things, the NSF asks respondents how much R&D they spent in each "product field." The vast majority of these product fields correspond to categories of equipment. The industry aggregates of this data are

[7] It was not conducted in 65, 66, 69, 78, 80, 82, 84, 86, 88, 90, 92, 94, and 96.

published in the NSF's *Funds for Research and Development in Industry*.[56] Unfortunately, there are many holes in the data due to non-disclosure of certain values and changes in the product field classification over time. These holes were filled in by imputation using available information in adjacent years. Data for years in which the survey was not done were interpolated.

Another discontinuity in the data comes from the fact that after 1983, R&D by product field was no longer imputed for non-respondents of the survey. Fortunately, the NSF does supply the coverage ratios so that total R&D by product field can be approximated under the assumption that non-respondents have a similar product field decomposition of their total R&D as have respondents. After these adjustments were made to the raw data, what was left was a matrix of applied R&D by product field for 1957-97. For the purposes of this project I was only interested in the R&D applied to equipment product fields and thus I omit from this matrix rows corresponding to non-equipment fields (e.g. Chemicals). The field "Electrical Equipment" contains one subfield, "Electronic Components," whose applied R&D consists mainly of semiconductor research. In the LRD (as well as in the NIPA), semiconductors are considered an intermediate input rather than a capital asset and therefore I subtracted out all "Electronic Components" product field R&D from that of "Electrical Equipment."

As discussed in Section 4, the type of R&D that causes downstream productivity gains is the product-oriented type. Unfortunately, the NSF survey does

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[8] Hard copies of the tables, one for each year of the survey, containing total R&D by product field, were generously compiled and provided by Raymond Wolfe of the NSF.

not distinguish between product- and process-oriented R&D. Scherer (1984), however, does provide a detailed industry-level table of the percentages of issued patents, sampled between June 1976 and March 1977, that were product-oriented. Using Scherer's table, I aggregated these percentages to the NSF product field level by taking weighted averages of the percentages for the component industries that comprise a product field. For each component industry, the weight was its 1974 R&D divided by the 1974 R&D for the product field as a whole. 1974 was the appropriate year here since the sampled patents were applied for, on average, in 1974. It seems reasonable to assume that the split between process- and product-orientation in patents is similar to that in R&D and also that this split is relatively stable over time. Subject to these assumptions, the resulting share of each product field's R&D that is product-oriented is shown in Table 3-3. The shares are quite high with the lowest, 77.5%, occurring in "Aircraft and parts." Multiplying these shares by the corresponding product fields' R&D for 1957-97 gives the $r_p(t)$'s in equations (3-4) and (3-5) above.

**Table 3-3**
**Concordance between NSF Product Field and BEA Asset Type**

| NSF Product Field | Percent Product-Oriented | BEA Asset Type |
|---|---|---|
| Other fabricated metal products | 83.9 | Other fabricated metal products |
| Engines and turbines | 91.7 | Internal combustion engines |
| | | Steam engines |
| Farm machinery and equipment | 98.3 | Agricultural machinery, except tractors |
| | | Farm tractors |
| Construction, mining, and materials handling machinery | 99.1 | Construction tractors |
| | | Construction machinery, except tractors |
| | | General industrial, including materials handling, equipment |
| | | Mining and oilfield machinery |
| Metalworking machinery and equipment | 98.5 | Metalworking machinery |
| Office, computing, and accounting machines | 94.5 | Mainframe computers |
| | | Personal computers |
| | | Direct access storage devices |
| | | Computer printers |
| | | Computer terminals |
| | | Computer tape drives |
| | | Computer storage devices |
| | | Other office equipment |
| Other machinery, except electrical | 96 | Special industry machinery, n.e.c. |
| | | Service industry machinery |
| Electrical equipment | 81.8 | Electrical transmission, distribution, and industrial apparatus |
| | | Communication equipment |
| | | Household appliances |
| | | Other electrical equipment, n.e.c. |
| Motor vehicles and equipment | 94.9 | Autos |
| | | Trucks, buses, and truck trailers |
| Other transportation equipment | 99.5 | Ships and boats |
| | | Railroad equipment |
| Aircraft and parts | 77.5 | Aircraft |
| Scientific and mechanical measuring instruments | 97.5 | Instruments |
| Optical, surgical, photographic, and other instruments | 93.2 | Photocopy and related equipment |

The other data ingredient necessary for creating the desired embodied R&D

indices is a capital flows matrix by year. I use the BEA's unpublished table of nominal investment by asset type for 62 industries for 1957-97 provided in the *Fixed Reproducible Tangible Wealth in the United States, 1925-1997*.[57] First, a many-to-one mapping was made between the BEA's asset types and the NSF's equipment product fields. This mapping is shown in Table 3-3. The mapping was used to convert the capital flows matrix to one that is by product field rather than by asset type. This flows matrix was then converted into a coefficients (shares) matrix using the industry investment totals (over all equipment product fields). The elements of this matrix correspond to the $x_{pi}$'s in equations (3-3) and (3-5) above.

The $x_{pi}$'s and $r_p$'s are used, as prescribed by equations (3-3), (3-4), and (3-5), to construct each of the two indices. The depreciation rate, d, is assumed to equal 15%, which is commonly used in the R&D literature when direct R&D stocks are constructed. There is also evidence that, at least for R&D directed towards an industry's product (rather than its capital), a depreciation rate closer to zero may be more appropriate (see Griliches and Lichtenberg (1984)). Therefore, as an alternative, I also construct indices using a 2% depreciation rate. The choice turns out to have very little effect on the growth of an index or its correlation with the Solow Residual or

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[9] Investment in non-equipment asset types was dropped from the matrix. Of the 37 BEA asset types, only the 35 which referred to equipment assets were kept. Thus, the embodied R&D indices I construct exclude R&D embodied in structures. This is appropriate since $\gamma$ refers only to embodied technological change in equipment. In addition, 4 of the 35 equipments assets were dropped from the matrix as well because they could not be mapped to any NSF product field. These were "Household Furniture," "Other Furniture," "Nuclear Fuel Rods," and "Other Nonresidential Equipment."

estimated $\gamma$. For both of these stocks, a unit bucket adjustment is made to "fill in" the stock for early periods (see Almon (1998), p. 87).

Table 3-4 shows the annual growth rate of $\Phi^1$ (assuming a 15% depreciation rate) for each industry from 1972-96, ranked in descending order. 1972-96 is the relevant period for comparing embodied R&D to $\gamma$ since $\gamma$ refers to the rate of embodied technological change between 1972-96. The annual growth for the overall economy, shown at the bottom of the table, has been about 2%. Notice that services, particularly financial services, tend to have the fastest growth in embodied R&D while manufacturing industries exhibit far slower growth. This could be because services have been changing their capital asset mix, relative to manufacturing, towards higher-tech equipment (e.g. computers), or because the equipment goods that service industries traditionally invest in have undergone rapid increases in R&D (causing high growth in $q_p$), or both. More generally, it would be useful to know for the overall economy, as well as for individual industries, whether the growth in embodied R&D over the past few decades is driven more by changes in capital composition or growth in R&D spending.

The following equation provides just such a decomposition:

$$\begin{aligned}\Delta\Phi^1 &\equiv \Phi^1(T_1) - \Phi^1(T_0) \\ &= \sum_p \Delta q_p \cdot x_{pi}(T_0) + \sum_p \Delta x_{pi} \cdot q_p(T_0) + \sum_p \Delta x_{pi} \cdot \Delta q_p\end{aligned}$$

[Equation 3-6]

The first term in the decomposition captures the contribution to total change from changes in R&D embodied in capital goods holding constant the composition of capital. The second term gives the contribution from changes in asset mix holding constant R&D embodied in specific goods. The third is an interaction term, giving the contribution from the covariance of changes in R&D embodied in goods with changes in asset mix. Dividing both sides of (9) by $\Phi^1(T_0)$ yields a growth rate decomposition.

Figure 3-1 graphs this decomposition for the 1972 to 1997 growth rates across industries. The industries are ordered from left to right according to their total growth rate. The figure also gives the unweighted averages across industries. The chart shows that the primary driver of increases in embodied R&D, as measured by $\Phi^1$, has been increases in R&D spent on equipment assets rather than changes in asset mix. We can also see that the difference in embodied R&D growth between those industries with high growth such as services and those with low growth such as manufacturing, is primarily due to fact that high growth industries channel a higher fraction of their total investment into goods whose embodied R&D is growing rapidly. It is *not* because they have been changing the composition of the goods in which they invest.

Recall that the $q_p$'s that go into the equation for $\Phi^1$ were normalized, as theory dictates, to equal one in the base year of the price deflator. This is because the real marginal product of investment must be equal across asset types.[58] This means that by construction $\Phi^1(t)$, which is just a weighted average of the $q_p$'s, will be one in the base

[10] Consider a simple Cobb-Douglas production function where there are two types of capital goods 1 and 2: $Y_t = K_t^{\alpha} L_t^{\beta}$ where $K_t = K_{t-1}(1-\delta) + i_t^1 q_t^1 + i_t^2 q_t^2$. In the base year, the marginal product of a current dollar's worth of investment is identical to the marginal product of a constant-quality unit of investment as quality is defined relative to the base year's level. The marginal product of a current dollar's worth of investment in good j ($i^j$) is $\alpha Y q^j/K$. Equalizing across goods yields $q^1 = q^2$. In non-base years, the equality between nominal and real marginal products breaks down and thus $q^1$ need not equal $q^2$.

year. Therefore, differences across industries in the *level* of $\Phi^1$ only imply interindustry differences in the *growth* of embodied R&D relative the base year.

The base year value of index $\Phi^2$, on the other hand, does not necessarily have to be equal across industries nor equal to one. This is true whether $\Phi^2$ is proportional to the true industry $q_i$ or to the true industry $\gamma_i$. Neither $q_i$ nor $\gamma_i$ must be equal across industries, even in the base year. Nonetheless, since the actual levels of $\Phi_i^2$ (t) are only meaningful in their relation to index values for other years or industries, I normalize $\Phi_i^2$ (t) to be one for the average value (over the 1972-96 period) of the index for the overall private economy. All $\Phi^2$'s are thus relative to the average extent of R&D embodied in capital economy-wide.

## Table 3-4 Growth in $\Phi^1$

| Industry | Annual Growth in $\Phi^1$ from 1972-96 |
|---|---|
| Federal reserve banks | 0.060 |
| Security and commodity brokers | 0.057 |
| Financial holding and investment offices | 0.056 |
| Legal services | 0.054 |
| Educational services | 0.054 |
| Nonfinancial holding and investment offices | 0.050 |
| Insurance carriers | 0.048 |
| Other services, n.e.c. | 0.045 |
| Insurance agents, brokers, and service | 0.041 |
| Trucking and warehousing | 0.039 |
| Local and interurban passenger transit | 0.037 |
| Pipelines, except natural gas | 0.037 |
| Auto repair, services, and parking | 0.032 |
| Wholesale trade | 0.031 |
| Construction | 0.030 |
| Metal mining | 0.029 |
| Other depository institutions | 0.028 |
| Miscellaneous repair services | 0.028 |
| Transportation services | 0.027 |
| Industrial machinery and equipment | 0.026 |
| Gas services | 0.026 |
| Oil and gas extraction | 0.026 |
| Business services | 0.025 |
| Water transportation | 0.025 |
| Electric services | 0.024 |
| Leather and leather products | 0.024 |
| Amusement and recreation services | 0.024 |

| | |
|---|---|
| Personal services | 0.024 |
| Agricultural services, forestry, and fishing | 0.023 |
| Tobacco products | 0.023 |
| Radio and television | 0.022 |
| Sanitary services | 0.021 |
| Retail trade | 0.021 |
| Nonmetallic minerals, except fuels | 0.021 |
| Telephone and telegraph | 0.021 |
| Coal mining | 0.021 |
| Railroad transportation | 0.020 |
| Real estate | 0.020 |
| Nondepository institutions | 0.019 |
| Health services | 0.019 |
| Motion pictures | 0.018 |
| Hotels and other lodging places | 0.017 |
| Petroleum and coal products | 0.017 |
| Other transportation equipment | 0.016 |
| Electronic and other electric equipment | 0.016 |
| Instruments and related products | 0.016 |
| Printing and publishing | 0.016 |
| Farms | 0.015 |
| Lumber and wood products | 0.015 |
| Apparel and other textile products | 0.014 |
| Miscellaneous manufacturing industries | 0.014 |
| Stone, clay, and glass products | 0.014 |
| Chemicals and allied products | 0.014 |
| Furniture and fixtures | 0.013 |
| Food and kindred products | 0.013 |
| Paper and allied products | 0.013 |
| Primary metal industries | 0.012 |
| Fabricated metal products | 0.009 |
| Textile mill products | 0.006 |
| Rubber and miscellaneous plastics products | 0.005 |
| Motor vehicles and equipment | 0.005 |
| Transportation by air | 0.003 |
| **TOTAL** | 0.022 |

Table 3-5 displays the results of the construction of $\Phi^2$. Column 2 shows the mean level of the index over the 1972-96 period. The third column gives its annual growth rate over the same period. The industries are ordered according to their mean value of $\Phi^2$. For the overall economy, the growth rate of the index was about 3.3%. The ranking of industries seems quite reasonable. Transportation by air tops the list which is not unexpected since a great deal of R&D is done on airplanes.[59] One can also see that the service industries tend to be high on the list. Though services are not capital-intensive, what investments they do make tend to be in high-tech equipment such as computers. The bottom of the list also fits with our *a priori* notions of which industries tend to use relatively low-tech equipment. The final four are Construction, Coal Mining, Trucking and Warehousing, and Farms.

## Table 3-5 Growth and Mean of $\Phi^2$

| INDUSTRY | Mean $\Phi^2$ from 1972-96 | Annual Growth in $\Phi^2$ from 1972-96 |
|---|---|---|
| Telephone and telegraph | 1.644 | 1.673 |
| Radio and television | 1.596 | 1.738 |
| Transportation by air | 1.569 | -0.100 |
| Security and commodity brokers | 1.286 | 4.988 |
| Legal services | 1.284 | 4.713 |
| Trucking and warehousing | 1.243 | 3.997 |
| Insurance agents, brokers, and service | 1.238 | 4.408 |
| Financial holding and investment offices | 1.184 | 4.473 |
| Business services | 1.149 | 3.222 |
| Local and interurban passenger transit | 1.124 | 2.798 |
| Hotels and other lodging places | 1.122 | 3.999 |
| Other services, n.e.c. | 1.121 | 4.796 |
| Insurance carriers | 1.119 | 3.688 |
| Nonfinancial holding and investment offices | 1.115 | 3.752 |
| Wholesale trade | 1.101 | 4.436 |
| Pipelines, except natural gas | 1.075 | 2.645 |
| Auto repair, services, and parking | 1.075 | 4.489 |
| Other depository institutions | 1.072 | 2.802 |
| Real estate | 1.044 | 4.172 |
| Health services | 1.022 | 3.568 |
| Educational services | 1.020 | 3.348 |
| Amusement and recreation services | 1.017 | 2.390 |
| Electric services | 1.014 | 1.751 |
| Federal reserve banks | 1.004 | 3.094 |
| Miscellaneous repair services | 0.986 | 6.658 |
| Personal services | 0.905 | 4.252 |
| Electronic and other electric equipment | 0.880 | 1.801 |
| Nondepository institutions | 0.865 | 5.049 |
| Retail trade | 0.854 | 4.177 |
| Gas services | 0.847 | 3.393 |

[11] The value of embodied R&D in "Transportation by air" may be artificially high since the R&D on aircraft includes R&D on military planes financed by the Defense Department.

| | | |
|---|---|---|
| Industrial machinery and equipment | 0.772 | 3.763 |
| Apparel and other textile products | 0.714 | 2.008 |
| Other transportation equipment | 0.699 | 4.223 |
| Metal mining | 0.678 | 4.189 |
| Agricultural services, forestry, and fishing | 0.676 | 2.899 |
| Sanitary services | 0.660 | 4.141 |
| Construction | 0.637 | 5.665 |
| Motion pictures | 0.620 | 5.939 |
| Instruments and related products | 0.579 | 6.202 |
| Railroad transportation | 0.577 | 5.414 |
| Stone, clay, and glass products | 0.565 | 4.381 |
| Transportation services | 0.564 | 8.177 |
| Primary metal industries | 0.548 | 2.035 |
| Leather and leather products | 0.548 | 3.755 |
| Tobacco products | 0.528 | 3.595 |
| Printing and publishing | 0.525 | 3.950 |
| Furniture and fixtures | 0.523 | 3.978 |
| Oil and gas extraction | 0.520 | 4.135 |
| Lumber and wood products | 0.507 | 2.293 |
| Petroleum and coal products | 0.501 | 0.581 |
| Chemicals and allied products | 0.499 | 2.015 |
| Paper and allied products | 0.492 | 0.995 |
| Food and kindred products | 0.486 | 2.566 |
| Miscellaneous manufacturing industries | 0.462 | 4.314 |
| Nonmetallic minerals, except fuels | 0.438 | 0.426 |
| Fabricated metal products | 0.382 | 1.817 |
| Textile mill products | 0.358 | 2.379 |
| Coal mining | 0.326 | 3.471 |
| Water transportation | 0.321 | 7.174 |
| Farms | 0.307 | 3.947 |
| Motor vehicles and equipment | 0.271 | 2.976 |
| Rubber and miscellaneous plastics products | 0.265 | 2.582 |
| **TOTAL** | 1.000 | 3.303 |

## 6. Is Embodied R&D related to Estimates of Embodied Technology?

In section 5 I argued that $\Phi^1$ should proxy for the level of embodied technology and therefore its growth rate should proxy for the rate of embodied technological change ($\gamma$). I also argued that either the level or the growth rate of $\Phi^2$ should be proportional (though not necessarily serve as a proxy) to $\gamma$. Table 3-6 shows the ordinary and Spearman's rank correlations, among the 22 manufacturing industries, between $\hat{\gamma}$ and each of 3 variables: 1) the 1972-96 annualized growth in $\Phi^1$, 2) the 1972-96 annualized growth in $\Phi^2$, and 3) the 1972-96 mean of $\Phi^2$.[60] Neither of the growth rates appear to be correlated with $\hat{\gamma}$. Yet, the mean of $\Phi^2$ is positively correlated with $\hat{\gamma}$, with an ordinary correlation coefficient of 0.54, which is significant at the 99% level. The rank correlation is 0.42, significant at the 95% level.[61]

### Table 3-6 Correlation of Embodied R&D and $\hat{\gamma}$

| | Pearson's (ordinary) Correlation with $\hat{\gamma}$ (p-value) | Spearman's Rank Correlation with $\hat{\gamma}$ (p-value) |
|---|---|---|
| 1972-96 Annualized Growth rate of $\Phi^1$ | 0.070 (0.757) | 0.201 (0.370) |
| 1972-96 Annualized Growth rate of $\Phi^2$ | -0.248 (0.265) | -0.183 (0.416) |
| 1972-96 Mean of $\Phi^2$ | 0.506 (0.016) | 0.450 (0.036) |

Viewed as a test of the reasonableness of the industry-specific estimated rates of embodied technological change, this exercise yields mixed results. It is encouraging that we have found strong evidence that these estimated rates are positively and significantly correlated with observable patterns of R&D spent on capital goods. Yet, the nature of the correlation is not as one would expect. Whether these results reflect that interindustry differences in true embodied technological change are proportional to interindustry differences in the average level of embodied R&D (as defined by $\Phi^2$), or

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[12] The correlations shown refer to $\Phi^1$ and $\Phi^2$ constructed using a 15% depreciation rate. Assuming a 2% rate yields very similar results.

[13] Another interesting finding, not shown, is that the growth in $\Phi^1$ has a Pearson's correlation with the mean of $\Phi^2$ of 0.53 and a Spearman's rank correlation of 0.62, both of which are significant at the 99% level.

whether they imply that our $\hat{\gamma}$'s are actually capturing an industry's *level* of embodied technology and not its rate of change, is difficult to say.

A third possibility is that the growth rates of embodied R&D, as measured by growth in either $\Phi^1$ or $\Phi^2$, are badly mismeasured since the time-series dimensions of both the BEA capital flows tables and the NSF product field R&D tables are highly suspect. The annual capital flows tables are based on input-output studies that 1) are only done every five years, and 2) are largely based on the occupational composition of industries, which may fluctuate due to reasons unrelated to capital mix. The NSF data underlying the annual R&D by product field tables constructed in this paper have many missing years that were filled in by interpolation as well as other discontinuities that had to be dealt with. For these reasons the time series dimension of the indices constructed in this paper may be less reliable than the cross-sectional dimension. This is especially problematic for $\Phi^1$ because the normalization that causes $\Phi^1$ to equal one in all industries in the base year implies its interindustry differences in levels are really determined by the time series movements. Interindustry differences in the level of $\Phi^2$, on the other hand, should be fairly reliable though differences across growth rates may not be. Nonetheless, this intertemporal measurement error can only explain the lack of correlation that $\Phi^1$ and the growth of $\Phi^2$ have with $\hat{\gamma}$; it cannot explain why the mean level of $\Phi^2$ would actually have a positive and significant correlation.

One way of sorting out whether the positive correlation between $\Phi^2$ and $\hat{\gamma}$ is due to $\hat{\gamma}$ measuring the level and not the growth rate of embodied technological change or rather is due to the level of $\Phi^2$ being a good predictor of the true rate of embodied technological change, is to go back to the data on product-oriented R&D by product field and ask whether it is the level or growth in R&D that predicts technological change at the product field level. Of course, there are no observables of true technological change so one must look to the literature for evidence on the rates of technological change in equipment assets. Gordon's (1990) major study of durable goods provides alternative price indexes for equipment from 1947-1983 which *inter alia* attempt to account for quality change. Hornstein and Krusell (1996) and others, using a 2-sector model of investment and consumption, argue that the growth rate of Gordon's aggregate producer durable equipment (PDE) price index relative to the consumption deflator is equal to the negative of the rate of embodied technological change. Thus, one can use the rate of relative price decline of each equipment product field, according to Gordon's indexes, as a proxy for the rate of technological change in that field.

From the 22 PDE categories for which Gordon constructed price indexes, I construct 13 Törnqvist price indexes corresponding to the 13 equipment product fields. I then compute the annual growth rates of these prices relative to the PCE deflator from 1957 (the R&D data does not begin until 1957) to 1983. These growth rates can be compared to the levels and growth rates of the $r_p$'s and $q_p$'s constructed above. It should be noted that an equipment asset's relative price may fluctuate not only due to technological change but also due to substitution effects between equipment assets. However, one would expect substitution between such broad product fields as those in Table 3-3 to be quite limited.

Table 3-7 shows the ordinary and rank correlations between the relative decline of Gordon's price indexes to three variables defined over the 1957-1983 period: 1) growth of $q_p$, 2) growth of $r_p$, and 3) mean of $r_p$. The correlations are perfectly consistent with those found in Table 3-6. Again, it is the mean level of R&D and not its growth rate that is strongly related to technological growth. The mean of product-oriented R&D applied to an equipment type ($r_p$) has a negative correlation with the growth rate of that equipment type's relative price of -0.504 (significant at the 10% level) and a negative rank correlation of -0.674 (significant at the 5% level). The correlations pertaining to other two variables are insignificantly different from zero.

**Table 3-7**

**Correlations between R&D Stocks and Relative Price Change**

| | Pearson's (ordinary) Correlation with the relative growth rate of Gordon's price indexes (p-value) | Spearman's Rank Correlation with the relative growth rate of Gordon's price indexes (p-value) |
|---|---|---|
| Annual growth from 1957-83 in $q_p$ | 0.016<br>(0.958) | 0.206<br>(0.498) |
| Annual growth from 1957-83 in $r_p$ | -0.115<br>(0.710) | 0.185<br>(0.546) |
| Mean $r_p$ over 1957-83 | -0.504<br>(0.079) | -0.674<br>(0.012) |

## 7. Relationship Between Embodied R&D and the Solow Residual

To further investigate whether the positive correlation found above between (average) $\Phi^2$ and $\hat{\gamma}$ is indicative of a true relationship between $\Phi^2$ and embodied technological change, we can see if either the growth or level of $\Phi^2$ is a good predictor of the Solow Residual.[62] If there is embodied technological change, the Solow Residual (SRD) will be an upwardly biased estimator of true total factor productivity (TFP) growth. This bias is larger the larger is $\gamma$. Therefore, if the indices are positively proportional to the true $\gamma$, then they should have a positive effect on SRD.

The panel nature of the measured data on $\Phi^1$ or $\Phi^2$ allows us to separately investigate the effect of these indices on SRD over the cross-industry dimension (emphasizing long-run/growth patterns), the time-series dimension (emphasizing short-run fluctuations), or both.[63] The cross-industry relationship can be estimated using a "between" regression which regresses the intertemporal mean of the dependent variable on the intertemporal mean of the regressor. A "within" regression isolates the time-series relationship by regressing the dependent variable net of its intertemporal mean on a similarly demeaned regressor. Lastly, I estimate the total effect via a first-difference regression: the change in the dependent variable between t and t-1 regressed on the change in the independent variable. The first-differencing simply allows for the intercept to vary by industry.

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[14] Defined as $d\log(Y) - c_L d\log(L) - c_J d\log(J) - c_S d\log(S) - (1- c_L- c_J-c_S)d\log(M)$, where Y is gross output, L is labor, J is equipment, S is structures, and M is materials. $c_i$ is the share of input i in total costs. Data on real equipment investment, structures investment, and materials come from the BEA. Equipment and structures capital stocks were constructed via the perpetual inventory methods using industry-level physical depreciation schedules derived from the Federal Reserve Board's Capital Stock study (Mohr and Gilbert (1996)). Cost shares for equipment and structures are constructed according to the Hall-Jorgenson user cost of capital formula using data from BEA. Data on real output, labor, and hourly labor compensation come from either the Annual Survey of Manufacturers (Census), Bureau of Labor Statistics (BLS), or the BEA depending on the industry. See Appendix B for a list of data sources for output.

[15] See Griliches and Mairesse (1995) for a discussion of the advantages and disadvantages of different panel data estimation techniques.

Table 3-8 shows the results from estimating these three different types of regressions. The dependent variable in these regressions is the Solow Residual. The first column lists the independent variable used. The estimated coefficient (and standard error) on that variable, when all industries are included in the regression, is shown in the second column. The independent variable (aside from the constant), which is denoted X in the table, is one of the three variables whose average I compared to $\hat{\gamma}$ in Section 6 and Table 3-6. They are the level of $\Phi^2$, the growth of $\Phi^2$, and the growth of $\Phi^1$. The signs and confidence intervals found in the between regression, which is the most comparable to the simple correlations of Table 3-6, are quite similar to those estimated correlations.[64] Yet again, the mean of $\Phi^2$ is the only variable found to be positive and significant. This seems to lend even further support to the hypothesis that the positive correlation found between $\hat{\gamma}$ and the mean level of $\Phi^2$ is due to $\Phi^2$ being a good predictor of true embodied technological change, rather than $\hat{\gamma}$ inadvertently capturing the level and not the growth in embodied technology.

[16] The $R^2$ for this regression is 0.22, implying that 22% of the cross-industry variation in the Solow Residual can be explained by variation in embodied R&D as measured by $\Phi^2$.

## Table 3-8 Regressions of Solow Residual on Embodied R&D

| X | Estimate of $B_1$ (std error): All Industries (n=55) | Estimate of $B_1$ (std error): Manufacturing Subset (n=32) |
|---|---|---|
| "Between" Regression: $\overline{SRD_i} = B_0 + B_1 \cdot \overline{X_i} + \varepsilon_i$ | | |
| $\Phi^2$ | 0.518*** (0.135) | 0.544 (0.333) |
| $d\log(\Phi^2)$ | -0.139 (0.089) | -0.211 (0.144) |
| $d\log(\Phi^1)$ | -1.327 (8.312) | -21.314 (17.995) |
| "Within" Regression: $SRD_{it} - \overline{SRD_i} = B_0 + B_1 \cdot (X_{it} - \overline{X_i}) + \varepsilon$ | | |
| $\Phi^2$ | 0.001 (0.002) | 0.0055** (0.0027) |
| $d\log(\Phi^2)$ | 0.032* (0.018) | 0.0214 (0.0217) |
| $d\log(\Phi^1)$ | -0.002 (0.021) | -0.0010 (0.0238) |
| Total/First-difference: $SRD_{it} - SRD_{it-1} = B_0 + B_1 \cdot (X_{it} - X_{it-1}) + \varepsilon_i$ | | |
| $\Phi^2$ | 0.030* (0.017) | 0.0563** (0.0260) |
| $d\log(\Phi^2)$ | 0.035** (0.018) | 0.0555*** (0.0212) |
| $d\log(\Phi^1)$ | 0.017 (0.025) | 0.0077 (0.0324) |

* - significant at the 10% level.
** - significant at the 5% level.
*** - significant at the 1% level.

The within and first-difference regressions find no significant effect of these indices on SRD. This may be due to the intertemporal measurement errors, discussed above, that are likely in the data on $\Phi^1$ and $\Phi^2$.

On the Solow Residual side of the equation, data, particularly real output data, outside of manufacturing is generally considered less reliable than manufacturing data. Thus, the third column gives the estimated coefficients obtained when only manufacturing industries are included. Now, $\Phi^2$ shows up as positive and significant in all three types of regressions (although in the between regression its coefficient is no longer significant at the 5% level but rather at the 10%). With but one exception, the growth rate of $\Phi^1$ or $\Phi^2$ again has no significant effect on SRD. The one exception is the growth rate of $\Phi^2$ in the first-difference regression.

These results are quite consistent with other studies on indirect R&D which generally find stronger effects on productivity in the cross-section than in the time-series. Interestingly, the results are also very similar to the findings of Bartelsman, Caballero, and Lyons (1994). They find that upstream suppliers' activity (as measured by cost-share-weighted input growth) does not have a significant effect on downstream productivity in their within estimates but does in their between estimates. It is possible that upstream activity is simply a good predictor of upstream R&D spending (or more broadly, upstream innovation), for they are certain to be correlated. Then, under the joint hypothesis that embodied R&D, as measured by $\Phi^2$, is proportional to embodied technological change and that capital good price deflators do not fully account for quality change, some of what Bartelsman, et al. find may be due to "spillovers" stemming from this price mismeasurement -- the same spillovers that cause upstream embodied R&D to have downstream effects on measured productivity.

Given our relative confidence in the measurement of the across-time means of $\Phi^2$, and their demonstrated correlation with $\hat{\gamma}$ and the Solow Residual, I then use these means to impute $\gamma$'s for nonmanufacturing industries (where $\hat{\gamma}$'s are not available) via the estimated relationship obtained from a linear regression across manufacturing industries of $\hat{\gamma}$ on a constant and the 1972-96 mean of $\Phi^2$.[65] This regression yielded the following:

$$\hat{\gamma} = \underset{(0.047)}{-0.036} + \underset{(0.051)}{0.054}\times(\text{mean } \Phi^2); \quad R^2 = 0.060.$$

The imputed values of $\gamma$ for nonmanufacturing sectors, computed using this estimated relationship, are shown in Table 3-9. There were five negative imputed values which were replaced with zero's. The $\gamma$'s range from 0 to 11%. The magnitudes and the cross-sectoral ranking of these rates of embodied technological change seem quite reasonable.

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[17] For this regression, I exclude "Computers" and "Electronic Components" which have unrealistic outlier $\hat{\gamma}$'s of 2.93 and 0.77, respectively.

### Table 3-9 Imputed $\gamma$'s for Nonmanufacturing sectors

| Sector Name | $\gamma$ |
|---|---|
| Agriculture, forestry, and fisheries | 0.008 |
| Metal mining | 0.025 |
| Coal mining | 0.000 |
| Natural Gas and Crude Petroleum extraction | 0.011 |
| Non-metallic mining | 0.003 |
| Construction | 0.021 |
| Railroads | 0.016 |
| Air transport | 0.106 |
| Other transportation | 0.055 |
| Communication services | 0.111 |
| Electric utilities | 0.056 |
| Gas utilities, and water and sanitary services | 0.032 |
| Wholesale trade | 0.064 |
| Retail trade, and restaurant and bars | 0.041 |
| Finance and Insurance | 0.064 |
| Real Estate | 0.058 |
| Hotels, and personal and repair services (exc. auto) | 0.055 |
| Business services | 0.074 |
| Automobile services | 0.061 |
| Movies and amusement parks | 0.038 |
| Medical services | 0.056 |
| Education, social services, membership organizations | 0.061 |

## 8. Conclusion

The title of this chapter asks "Is embodied technology the result of upstream R&D?" The answer seems to be a cautious yes. If the R&D applied to an industry's capital goods is not the actual *cause* of the industry's embodied technological change, it is at the very least highly correlated with whatever the true cause or causes are. This is evidenced by the finding that the extent of R&D embodied in an industry's capital is highly correlated with both the industry's estimated rate of embodied technological change as well as the industry's productivity growth as measured by the Solow

Residual. Furthermore, the extent of R&D applied to a particular capital good is found to be highly correlated to the relative decline in the price of that good, providing further evidence that technological advances in capital are the result of R&D oriented toward the creation of new capital goods. As for the possibility of reverse causation, given the lags between R&D and innovation it is difficult to imagine how increases in an industry's embodied technology could actually cause increased past and present R&D spending by upstream capital goods suppliers.

The results of this chapter show that data on upstream product-field R&D can be used to measure the relative differences among industries in their rates of embodied technological change, which are an inherently unobservable. Armed with estimates of embodied technological change in manufacturing industries, where plant-level longitudinal data is available, I was able to use the constructed measures of embodied R&D to impute rates of embodied technological change for nonmanufacturing industries. Thus, aside from its other contributions, this chapter provides the first industry-level estimates of embodied technological change spanning the entire private economy. With these estimates in hand, we are now ready to construct industry-level, *productive* equipment capital stocks and then use them to help estimate labor productivity equations.

# Chapter 4

## Embodying Embodiment in IDLIFT

## 1. Introduction

This chapter discusses proposed changes to IDLIFT, a large-scale structural macroeconomic model of the U.S. First, it provides some background into the structure of IDLIFT and the economic philosophy behind it. It then describes an effort to find a labor productivity equation for IDLIFT that follows the Neoclassical production theory, fits the industry-level time-series data well, and has sensible coefficients.

## 2. Brief Overview of IDLIFT

### A. Inforum Modeling in General

Since its founding in 1967 by Clopper Almon, Inforum[66] has been building, and encouraging others to build, regression-based structural macroeconomic models based on input-output relationships between industries. Inforum maintains two large-scale U.S. macro models (though one is essentially a more detailed extension of the other), a U.S. demographics projections model, and a bilateral trade model. It also works with partners from other countries in building and maintaining their own country models based on the Inforum modeling framework. Many of these are actually linked to the U.S. models via the bilateral trade model. Such a rich network of international and interindustry linkages makes Inforum models quite useful for a broad array of policy

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[1] Interindustry Forecasting at the University of Maryland.

analysis.  These linkages are also quite helpful in making successful long-term forecasts since both trade and input-output coefficients have important low-frequency movements over time.

Inforum models are members of the family of large-scale, regression-based macro models that also includes well-known U.S. models built by the Federal Reserve, Macroeconomic Advisers (formerly Laurence Meyer & Associates), DRI-McGraw-Hill, and WEFA.  The builders of these models all share the belief that for long-term forecasting and policy analysis, large-scale models (with hundreds of structural equations and identities) based on economic intuition are preferable to models with far fewer reduced-form equations based solely on past data.  The latter approach was put forth by Christopher Sims' (1980) influential *Econometrica* article which summarized the various arguments against large-scale macro models and introduced vector autoregression (VAR) as an alternative.  This article, combined with the well-known Lucas (1976) critique, had quite a dampening effect on the production and influence of structural models, particularly in the 1980's.  Though the reputation and usage of these models has never fully recovered from these theoretical attacks, their responses to the valid parts of the criticisms contained in these attacks as well as the lack of any viable alternatives have kept large-scale macro models alive and well into the new century.[67]

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[2] The VAR approach cannot be considered a viable alternative primarily because the estimation of a VAR system containing the hundreds, perhaps even thousands, of variables in many large-scale macro models is presently infeasible, both in terms of computational ability and theory.  In addition, most VAR models used today incorporate Bayesian *a priori* assumptions that are arguably as questionable as the assumptions of the structural model builder.  Moreover, "conditional" forecasts, i.e. those conditional on assumptions regarding policymaker behavior can only be done with a structural model, making nonstructural approaches like VAR ineffective for policy analysis (see Diebold (1998)).

On the opposite end of the spectrum of macroeconomic modeling from VAR are computable general equilibrium (CGE) models (of which the recent dynamic stochastic general equilibrium models are members). Not only are the functional forms of a CGE model's structural behavioral equations specified *a priori* by the model builder, as is the case with large-scale macro models, but the parameters of these equations are typically specified *a priori* as well. Moreover, the "structural equations" specified in a CGE model are generally of an altogether different nature than those of a large-scale macro model. The equations of a CGE model generally consist of the underlying utility and production functions at the microeconomic level. The parameters, of whose values CGE modelers believe they have *a priori* knowledge, are the fundamental taste and technology determinants.[68]

Regression-based structural macro models such as Inforum's thus lie somewhere between the CGE and VAR modeling approaches. They rely upon the notion that we, as economists, *do* have some valuable insight into the mechanisms of the economy but do not have an exact idea of the *quantitative* substance of these mechanisms. Hence, our economic intuition/theory can go a long way in helping us evaluate policy and predict the future course of the economy, yet we must rely on past data to better quantify our intuition.

The Inforum modeling philosophy differs from other large-scale macro models primarily in its utilization of input-output information in forming the overall structure of its models. Their input-output (IO) structure is both the blessing and the curse of

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[3] Calibration exercises are sometimes done to "estimate" these parameters, but this "estimation" cannot be said to be probabilistic in the sense that structural equations of large-scale macro models are probabilistically estimated (via regression).

these models. The curse is the tremendous effort required to maintain an adequate data foundation. However, as mentioned above, the IO structure allows a rich array of policy questions to be answered with the model, such as the overall effect on the steel industry of raising interest rates, incorporating the effect of interest rate hikes on the demand for both consumer and producer durables (e.g. automobiles). The IO structure also allows for a bottom-up approach to modeling the economy. That is, economic variables such as output and prices can be forecast at the industry-level, rather than economy-wide, and then aggregated to the macro-level. Thus, the IO structure of an Inforum model allows it to function in line with how the economy actually behaves.

### B. The IDLIFT Framework in Particular

Inforum's main model of the U.S. economy is IDLIFT, which is presently in the process of replacing its predecessor, LIFT (Long-term Interindustry Forecasting Tool).[69] In this section, I will discuss the general structure of the IDLIFT model as it currently stands. For a discussion of how IDLIFT differs from the LIFT model and planned future changes to the model (aside from those proposed in this dissertation), see Meade (1999).

The IDLIFT model forecasts output, employment, prices, exports, imports and interindustry flows for 97 commodity sectors (50 of which are in manufacturing); personal consumption expenditures (PCE) for 92 categories; equipment investment by 55 industries, construction spending for 19 categories; and the components of value-

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[4] The "ID" stands for Interdyme, the C++ framework developed at Inforum for building interindustry dynamic macroeconomic models (LIFT was built using Fortran).

added for 51 industries.[70] In addition, the model provides a full accounting of the macroeconomy. Macroeconomic variables such as the personal savings rate or the 3-month Treasury bill rate are estimated econometrically. Others are determined according to national accounting identities and still others are given to the model exogenously.

The overall structure of the model is based on the national accounting system embodied in the U.S. national income and product accounts (NIPA). There is a real side and a price side. On the real side, each component of final demand (i.e., the usual C+I+G+X-M) is modeled at the various levels of disaggregation mentioned above using structural behavioral equations. The disaggregate, sectoral equations have been estimated individually (as is the case with the labor productivity equations) or as a system (such as the PADS demand system for the consumption equations) using mainly industry-level time series data. Bridge matrices convert each of these final demand components from their particular level of disaggregation to the 97-sector commodity level. Sectoral (gross) output is then determined according to the fundamental input-output equation:

$$q = Aq + f \ , \tag{4.1}$$

where q is a 97×1 vector of output, A is the intermediate coefficient matrix (also called the input-output matrix or the requirements matrix), and f is the vector of final demand:

$$\begin{aligned} f_{97\times1} = H^{c}_{97\times92}c_{92\times1} + H^{eq}_{97\times55}eq_{55\times1} + H^{s}_{97\times19}s_{19\times1} \\ +i_{97\times1} + x_{97\times1} - m_{97\times1} + g_{97\times1}. \end{aligned} \tag{4.2}$$

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[5] These classification systems provide complete coverage of the economy.

The subscripts indicate the dimension of each matrix or vector. Here *c* denotes the consumption vector, *eq* denotes equipment investment by purchaser, *s* structures investment (construction) by type of structure, *i* inventory change, *x* exports, *m* imports, and *g* government spending.[71] $H^j$ is the bridge matrix for component j. A bridge matrix simply provides the concordance between two different sectoring schemes. All of the variables in equations (1) and (2) should rightly have time subscripts as well, including the A and H matrices which vary according to trends in the across-the-row totals. A detailed discussion of the equations or systems that forecast the components of the final demand vector is beyond the scope of this chapter.[72]

Given the forecasted vector of output ($q^*$), employment (number of jobs) by sector is computed as:

$$n^* = q^* \cdot \left( \frac{1}{(q/\ell)^*} \right) \cdot \left( \frac{\ell}{n} \right)^*, \qquad (4.3)$$

where $\ell$ is hours worked. An asterisk indicates that a variable is forecasted by the model. For instance, $\ell$ is not a variable in the model *per se* (it is determined by identity

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[6] In the model, government spending is actually decomposed into 5 components such as state and local spending, defense spending, etc. The macro-level of these components are generally exogenous to the model; the exogenous macro values are shared-out to the 97 sector level using the sectors' shares of that component of government spending from the most recent year of available data.

[7] For such a discussion, see Meade (1999).

once $[\ell/n]^*$ and $n^*$ are forecasted), but the average hours per job ($\ell/n$) and labor productivity ($q/\ell$) are. Employment forecasts, together with forecasts of the labor force, determine the unemployment rate, a key variable in the model. Aside from being extremely interesting in its own right, the unemployment rate affects many macroeconomic and industry equations on both the real and the income side of the model. By extension, then, it is evident that labor productivity is a key driver of the model (both through its effect on the model's unemployment rate and through its own direct presence in many model equations). The wide-ranging and powerful influence of the labor productivity equations in IDLIFT must be kept in mind throughout the chapter. It is the main motivation for the work proposed below.

On the income/price side of the model, prices at the 97-sector level are determined according to equations modeling the markups over unit intermediate and labor costs. Given this forecasted price row vector $p$ (1×97), value added by commodity sector is calculated as a residual using the dual of the fundamental input-output equation:

$$p = pA + v \,. \tag{4.4}$$

The components of value added (corporate profits, inventory valuation adjustment, capital consumption adjustment, net interest income, rental income, indirect taxes, government subsidies, and the big one: labor compensation) are each modeled separately. The forecasted values of the capital income components (everything except labor compensation) are then scaled to be consistent with equation (4.4) and the markup forecasts. Hourly labor compensation is modeled as a function of the growth in M2/GNP, the growth in **labor productivity**, and a supply shock (it is then multiplied by the forecast of the labor hours requirement, $\ell$, from the real side). So we can see that labor productivity gets its hands dirty on the income side of the model as well.

## 3. The Problem and Need for Change

With its considerable influence on labor compensation on the income side and employment and the savings rate on the real side, it should be evident by now that labor productivity is one of the most important variables in the IDLIFT model (as well as virtually any other large-scale structural macro model). Currently, the IDLIFT model's labor productivity equations are determined essentially by time trends and the difference between industry output and its previous peak, and does not contain any factor inputs as explanatory variables:

$$ln(q^i / l^i) = \beta_0^i + \beta_1^i t_1 + \beta_2^i t_2 + \beta_3^i qup + \beta_4^i qdown \qquad (4.5)$$

where: $t_1$ = a linear time trend starting in the first year of data;

$t_2$ = a second time trend, starting in 1972;

$qup_t = dq_t$, when $dq_t > 0$, 0 otherwise;

$qdown_t = -dq_t$, when $dq_t < 0$, 0 otherwise;

$dq_t = \ln(q_t) - \ln(qpeak_{t-1})$;

$qpeak_t = q_t$, if $q_t > qpeak_{t-1}(1-spill)$, otherwise $= qpeak_{t-1}(1-spill)$;

$spill$ = depreciation rate of capacity;

and i indexes the 55 industries/sectors.

Inforum has long had difficulty building into its models a sensible relationship between investment and labor productivity. Given that labor productivity is the key driver of the long-run output growth behavior of the model, the lack of an influence from investment or capital stock is lamentable. Virtually any neoclassical-based growth model attributes a substantial share of output growth to the growth of capital. Its omission from Inforum models, IDLIFT in particular, is due neither to a disbelief in neoclassical production theory nor to a lack of effort.

Many valiant attempts have been made over the years to develop and estimate productivity equations based on firm optimization behavior that incorporate the effects of changes in capital stock. These attempts have generally been foiled by one of two problems. First, in industry(sector)-level time-series regressions (with which the IDLIFT equations are typically estimated), the capital coefficient is often found to be either negative or positive but very close to zero (particularly in service sectors). Second, because the investment equations in IDLIFT have always been of a *flexible accelerator*-type nature (i.e. driven largely by current and lagged changes in output), the introduction of investment (via capital stock) into the productivity equations provided a seed for the explosion of output in the model's forecast. Any exogenous positive shock to the model caused output to grow, which caused investment to grow, which caused labor productivity to grow, which caused output to grow (mainly through productivity's increasing of the wage rate which lowers the savings rate which thus spurs consumption, the largest component of final demand),...ad infinitum. The model has lacked a supply constraint (such as a nonconvex adjustment cost in the investment equations) to put the brakes on investment and stabilize output.

For these reasons, IDLIFT's labor productivity equations (as well as those of other Inforum-type models) have heretofore remained essentially a series of time trends. Inforum's discontent with this situation has been around since its inception, as demonstrated here by the words of Almon (1969) describing an early version of IDLIFT's predecessor, LIFT:

> Until recently, our model has used *exogenous projections of labor productivity which were based on simple extrapolations of past trend*. This practice left an awkward hole in the middle of the model. For on the one hand, the endogenous generation of investment by industry was one of the distinguishing features of the model; and on the other hand, the *growth in labor productivity essentially determines the overall growth projection given by the model*. Even the most casual observation suggests that capital investment has something to do with the increase in labor productivity. Therefore, the absence of any connection between the two in the model struck people as a clear indication of ineptitude, or at least indolence on our part.
>
> The truth is that it is easier to recognize that there must be some connection than to measure the connection. We have made a number of false starts on the problem. ... At length, *we gave up the production approach to labor productivity -- although we retain it for capital investment -- because we couldn't make it work as well as the simple time trend equation*. (Italics added).

The above statement was quoted in Meade (1999) who went on to say: "Thirty years have passed since this remark, and we are no closer to a labor productivity equation that incorporates capital, research and development or any other significant influence we believe should be working." Developing just such an equation was one of the main motivations for the work presented in Chapters 2 and 3. It is argued below that the fruit of that work has allowed us to incorporate a Neoclassically-based labor productivity equation into IDLIFT while exceeding the fit and simulation properties of the former trend-based productivity equation.

The maintained hypothesis has been that one of the key problems with finding a successful Neoclassical equation has been mismeasurement of capital due to unobserved changes in embodied technology. It is well-known that classical measurement error causes an attenuation bias on the coefficient associated with the mismeasured independent variable. In fact, the problem is even worse. The measurement error in equipment capital that is caused by ignoring embodied technological change is not random; it is systematically related to the intertemporal investment distribution. The error will be greater the more an industry's capital is comprised of recent vintages. Recent investment will be positively correlated with other factor inputs such as labor. This will lead to an upward bias in the estimated labor elasticity. Furthermore, if constant returns to scale are imposed, this positive bias in labor elasticity imply a lower capital elasticity (in a value-added production function).

Thus, in order to correct this measurement problem, in the next section I construct quality-adjusted capital stocks using the $\gamma$'s found in Chapters 2 and 3 (estimated for manufacturing sectors, imputed for nonmanufacturing sectors). I then, in Section 5, estimate various labor productivity equations, some of which attempt to avoid the measurement error either by using the quality-adjusted capital stocks or by including the stock of embodied R&D along with unadjusted capital stock as an independent variable.

## 4. Constructing Quality-Adjusted Capital Stocks

At this point, it is important to be explicit about the objective I have in mind when constructing industry-level equipment capital stocks. The objective is not simply to produce historical time series of capital stocks that adjust for embodied technological change. If that were the case, one could simply use time series data on historical investment (from BEA), the estimated rates of embodied technological change from Chapters 2 and 3, and physical depreciation (constructed in Chapter 2 using FRB/BLS methodology) and apply the formula given in Equation (2-14). However, the fact that these stocks will need to be forecast in the IDLIFT model introduces a complication into how they must be constructed. The physical depreciation schedules, $D_{t,t-s}$, constructed in Chapter 2 and used to estimate embodied technological change ($\gamma$) are functions of both year and age. In order to "forecast" physical depreciation for future years, one must make some assumption regarding how $D_{t,t-s}$ will vary over t in the future.

What is needed is a time-invariant physical depreciation pattern to apply to the forecasted investment flows. One would also like this pattern to match as closely as possible the FRB/BLS physical depreciation schedules since these schedules were used in estimating $\gamma$ with the plant-level data. Thus, I use the average (over years and industries) age profile from those schedules (see Figure 2-2).

The average profile has a reverse-S shape. What I needed was a function with a minimal number of parameters that could mimic this reverse-S shape. I found such a function in the "cascading buckets" concept which is frequently utilized by users of the G regression software package (the package I used to estimate the time-series labor productivity equations). A cascading buckets system is a combination of several “bucket” functions. A single bucket is created by the use of the *@cum* function in G. The statement, $k_t$ = *@cum(*$k_t$, $i_t$, *z)*, defines the variable $k_t$ by the following equations:

$$k_0 = 0\ ; \qquad k_t = (1 - z)\cdot k_{t-1} + i_t \quad \forall t > 0 \tag{4-6}$$

The reverse-S shape can be obtained by a “cascading” of two or buckets, i.e. by having the outflow of the first bucket (here, $z\cdot k_{t-1}$) be the inflow (here, $i_t$) into the next bucket, then the outflow of the second bucket be the inflow into a third bucket, and so on.... The final function is the sum of these buckets.

In fact, even more variety of shape can be obtained by letting the inflow into the lower (i.e. second, third, ...) bucket “splatter out” or “miss” some of the lower bucket so that only $(z-\epsilon)\cdot k_{t-1}$ actually flows into it (and $\epsilon\cdot k_{t-1}$ is lost). Allowing some “splatter” turns out to be quite necessary for fitting the average physical depreciation schedule because without the splatter there would be no decrease in efficiency over the first N-1 years, where N is the number of buckets (i.e. without splatter, nothings falls out of the bucket system until there is no longer a lower bucket to catch the last bucket’s outflow). A decrease in efficiency beginning in the first year is a property of the age-efficiency schedule I am trying to fit.

Using the following three-bucket system, I was able to very closely replicate the age profile implied by the average physical depreciation schedule shown in Figure 2-2:

b1 = *@cum(*b1, *drop, A)*

b2 = *@cum(*b2, b1[1]**B, C)*

b3 = *@cum(*b3, b2[1]**A, C)*

where *drop* is a variable that is one at age 0 and zero thereafter and the notation [1] indicates a lag of 1 period.[73] Allowing B<A results in some of the outflow from b1 to splatter out or miss b2 allowing for efficiency loss immediately after the first year. I performed a grid search to find the parameters A,B, and C which resulted in the lowest sum of squared errors (SSE). The values A=.14, B=.129, and C=.3 led to a SSE < 0.001. Figure 4-1 shows the fitted values from this cascading bucket versus the actual depreciation schedule. Clearly, the fit is extremely close. This three-bucket system with the above parameter values became the $D_{t,t-s}$ used in the definition of the equipment capital stock given in equation (2-14). Now, rather than *drop* going into the first bucket, the actual equipment investment (adjusted for embodied technological change) flows in:

$$vi = (eqicu/pced)*(1+\gamma)^{t-t0}$$

$$b1 = @cum(b1, vi, 0.14)$$

$$b2 = @cum(b2, b1[1]*0.129, 0.3)$$

$$b3 = @cum(b3, b2[1]*0.14, 0.3)$$

$$J = b1 + b2 + b3$$

where *eqicu* is equipment investment in current dollar, *pced* is the PCE deflator, *vi* is vintage equipment investment adjusted for embodied technological change assumed to take place at the rate $\gamma$, and $J$ is the resulting quality-adjusted equipment capital stock.

## 5. Alternative Labor Productivity Equations

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[8] Actually, *drop(0)* is set equal to 0.989, the value of the average physical depreciation schedule at age 0. This value is slightly less than one due to the fact that the FRB allows for some wear-out in the first year of a capital good's life.

In this section, I perform a sort of “horse race” on several alternative equations and evaluate their performance in terms of average fit and the signs and magnitudes of the coefficient estimates. This approach of estimating a number of specific equations that are special cases of a more general model and choosing a single equation for forecasting based on economic and statistical criteria, is similar to the general-to-specific modeling approach recommended by David Hendry (2000).[74] The results indicate that equations using the quality-adjusted equipment stocks seem to outperform identical equations which use unadjusted stocks.

*A. Equations in Log-Levels and Including Materials*

In this subsection, I estimate 11 different specifications of a labor productivity equation for each of the 55 sectors in the IDLIFT investment sectoring scheme.[75] The average adjusted $R^2$, average estimated coefficients, and percent of coefficients that are positive are shown in Figures 4-2 through 4-5. With the exception of the former IDLIFT specification, all of the specifications are derived from a standard Cobb-Douglas Neoclassical production function:

$$Q_{it} = M_{it}^{\theta} L_{it}^{\beta} J_{it}^{\alpha} S_{it}^{\eta} \tag{4-7}$$

---

[9] General-to-specific modeling is also known as the LSE methodology. For references to this literature, see Hendry (1997), Hendry (1995), Hendry and Clements (1996), Hoover and Perez (1999), Ericsson and Marquez (1998), Cook and Hendry (1993). For a critique of general-to-specific modeling, see Faust and Whiteman (1997).

[10] Actually industries 6 (Construction) and 55 (Scrap and used equipment) are omitted due to lack of data.

The table below (4-1) gives a guide to the notation used in this equation as well as the other equations in this section.

## Table 4-1 Notation Guide

| Variable | Abbreviation | Elasticity of Output with respect to the variable |
|---|---|---|
| Real Output (log) | $Q$ ($q$) | -- |
| Real Materials, including Energy (log) | $M$ ($m$) | $\Theta$ |
| Labor (log) | $L$ ($\ell$) | $\beta$ |
| Real Equipment Stock (log) | $J$ ($j$) | $\alpha$ |
| Real Structures Stock (log) | $S$ ($s$) | $\eta$ |
| Embodied R&D Index (log) | $R$ ($r$) | $\sigma$ |
| Real Energy Expenditures | $E$ ($e$) | -- |
| Elasticity of Energy/Capital w.r.t. Utilization | $\tau$ | -- |

Some specifications attempt to proxy for unobserved variation in capital utilization in the manner as was done in Chapter 2 (see equations (2-11) and (2-12)). As described in Chapter 2, the utilization rate of equipment is assumed to be an increasing function of the energy-equipment ratio (likewise for the utilization rate of structures). It is assumed that in order to increase utilization by 1%, one must increase the energy-equipment ratio by $\tau$%. The special case $\tau = \infty$ means that there is no variation in utilization; $\tau = 1$ means energy use is perfectly proportional to capital services; and $\tau = 0$ means an infinitesimal change in the energy-equipment ratio will fully adjust utilization to the desired level.

The eleven specifications that I compare are as follows (the number preceding each will be used hereafter as labels):

1) Standard Neoclassical, Cobb-Douglas Production Function:

$$q - \ell = b_0 + (\beta - 1)\ell + \theta m + \alpha j + \eta s$$

2) Standard and adjusting to control for utilization using energy:

$$\mathrm{q} - \ell = \mathrm{b}_0 + \left(\frac{\beta - 1}{\beta}\right)\ell + \left(\frac{\theta}{\beta}\right)\mathrm{m} + \left(\frac{\alpha(\tau - 1)}{\beta\tau}\right)\mathrm{j} + \left(\frac{\eta(\tau - 1)}{\beta\tau}\right)\mathrm{s} + \left(\frac{\alpha + \eta}{\tau}\right)\mathrm{e}$$

3) Standard with constant returns to scale (RTS) imposed:

$$q - \ell = b_0 + \theta(m - \ell) + \alpha(j - \ell) + \eta(s - \ell)$$

4) Standard with constant RTS and adjusting for utilization using energy:

$$q - \ell = b_0 + \theta(m - \ell) + \left(\frac{\alpha(\tau - 1)}{\tau}\right)(j - \ell) + \left(\frac{\eta(\tau - 1)}{\tau}\right)(s - \ell) + \left(\frac{\alpha + \eta}{\tau}\right)(e - \ell)$$

5) Old IDLIFT equation:

$$\ell - q = b_0 + a_1 * t + a_2 * t^2 + a_3 * qup + a_4 * qdown$$

where *qup* and *qdown* are defined in equation (4.5).

6) Same as 1 but with *J* <u>not</u> adjusted for embodied technological change (i.e. *J* is constructed with $\gamma$=0 for all sectors).

7) Same as 2 but with *J* <u>not</u> adjusted for embodied technological change (i.e. *J* is constructed with $\gamma$=0 for all sectors).

8) Same as 3 but with $J$ <u>not</u> adjusted for embodied technological change (i.e. $J$ is constructed with $\gamma$=0 for all sectors).

9) Same as 4 but with $J$ <u>not</u> adjusted for embodied technological change (i.e. $J$ is constructed with $\gamma$=0 for all sectors).

10) Same as 8 but also include the log of embodied R&D:

$$q - \ell = b_0 + \theta(m - \ell) + \alpha(j - \ell) + \eta(s - \ell) + \sigma(r - \ell)$$

Here I assume that factor payments must be made to embodied technology just as they are for traditional capital and any other *internal* factor of production (i.e. embodied R&D is not a public good or externality), therefore constant RTS now means $\beta + \theta + \alpha + \eta + \sigma = 1$.

11) Same as 10 but adjusting for utilization using energy

$$q - \ell = b_0 + \theta(m - \ell) + \left(\frac{\alpha(\tau - 1)}{\tau}\right)(j - \ell) + \left(\frac{\eta(\tau - 1)}{\tau}\right)(s - \ell) + \left(\frac{\alpha + \eta}{\tau}\right)(e - \ell) + \sigma(r - \ell)$$

It should be noted that in this equation the embodied R&D index, unlike the stocks of equipment and structures, is assumed to have a constant rate of utilization.

Figures 4-2 through 4-5 summarize the results of estimating these 11 equations for all of the 55 sectors in IDLIFT (spanning the U.S. private economy). Given that data mismeasurement is generally considered to be more serious in nonmanufacturing industries and that the $\gamma$'s used for constructing equipment stock in these industries are imputed, it is helpful to look also at the results separately just for nonmanufacturing sectors. Thus, results for the subset of nonmanufacturing industries are summarized in Figures 4-6 through 4-9. In the following discussion, I will generally focus on the results for all sectors, though I will point out things that are substantially different in the nonmanufacturing subset.

Several important findings are apparent from the figures:

- As shown in Figure 4-2, all but specification 5 have very high adjusted-$R^2$'s (averaged over sectors). This result is due to the presence of intermediate inputs which have very high explanatory power. Because of the lack of intermediate inputs, the former IDLIFT labor productivity equation (5) has a much lower adjusted $R^2$ on average than those of the Neoclassical-type equations.
- Including energy to adjust for capital utilization does improve the average adjusted $R^2$ in all specifications (compare 1 vs. 2, 3 vs. 4, 6 vs. 7, and 8 vs. 9). This adjustment seems to have a minimal impact on both $\alpha$ and $\eta$ (in terms of their average estimate and their likelihood of being positive) except in specifications 4 and 11 which appear to generate some substantial outliers (see Figures 4-3 and 4-4) None of the specifications yields an average $\tau$ greater than 1 (as theory predicts). However, there appears to be enormous variation in the estimated $\tau$ across industries and for each specification the majority of $\tau$'s are positive.
- Including embodied R&D and unadjusted J as separate inputs results in a higher average adjusted $R^2$ than when unadjusted J is by itself (compare 10 vs. 8 and 11 vs. 9). In fact, the former also results in a slightly better average fit than when a quality-adjusted J alone is used (compare 10 vs. 3 and 11 vs. 4). As shown in Figure 4-3, the average coefficient on embodied R&D ($\sigma$) is approximately zero when utilization is not adjusted for. The combination of having embodied R&D as a separate regressor and adjusting for utilization appears to cause some nonsensical

outliers and a great many negative estimated $\sigma$'s. Compared to specifications 3 or 8, including embodied R&D in addition to unadjusted J (specification 10) reduces the average value and likelihood of positivity for the equipment elasticity ($\alpha$) and the structures elasticity ($\eta$). Making the same comparison for specifications that control for utilization (i.e. specifications 4 or 9 vs. specification 11), one finds that the positivity is again reduced for $\alpha$ and $\eta$, but the effect on their average elasticities is ambiguous due to a number of sizable outliers

- Aside from the outliers in $\alpha$ produced with specification 4, the estimated factor elasticities do not seem to be greatly affected by the adjustment of equipment capital for embodied technological change.
- The average estimate of the materials elasticity ($\theta$) is quite high in all specifications and is almost always positive.
- In nearly all cases, the likelihood of positivity for both $\alpha$ and $\eta$ is higher when returns to scale are constrained to be one (compare 1 vs. 3, 2 vs. 4, 6 vs. 8, and 7 vs. 9).
- Across all specifications, there is a disturbingly low percentage of estimated factor elasticities that are positive with the key exception of materials' elasticity.

In summary, I find that for the most part adjusting equipment capital for quality using my $\gamma$'s substantially improves the fit and sensibility of the labor productivity equation. Furthermore, controlling for utilization using the energy to capital ratio improves the fit and raises the estimated elasticities of structures, but it reduces the elasticities of equipment. Despite some loss of fit, imposing constant RTS seems to greatly improve the sensibility of the estimates. The beneficial effects of imposing constant RTS on $\alpha$ and $\eta$ seem to easily outweigh the cost of a slightly lowered fit. Finally, including embodied R&D improves the average fit slightly but has a substantial deleterious effect on the capital elasticities.

Based on these findings, it seems reasonable to drop from our consideration all but specifications 3, 4, 10, and 11. That is, we can feel comfortable hereafter imposing constant RTS and adjusting equipment capital by constructing the stock according to the $\gamma$'s found in Chapters 2 and 3 or by including embodied R&D as an additional independent variable (although these embodied R&D specifications do seem to yield less realistic estimates). Furthermore, adjusting for utilization seems to be a slight improvement over not controlling for it in terms of fit, so I will retain equation 4 for now despite its tendency to produce outlying unrealistic capital elasticities.

*B. Equations Omitting Intermediate Inputs*

It is often the case in production function or productivity regressions that intermediate inputs (materials) dominate the explanatory power of the independent variables and obscure the effects of the other inputs. As evidenced by the very high average $\theta$ and enormous mexval's (marginal explanatory power, not shown) for the coefficient on materials obtained in the regressions described above, this domination by materials appears to be the case in our regressions as well. Furthermore, the measures on real materials used in the above regressions are constructed by taking the column sum of a constant dollar input-output flow matrix. That is, real materials for industry j is $m_{jt} = \sum_i a_{ijt} q_{jt}$ where $a_{ijt}$ is element (i,j) in the intermediate coefficient matrix (A in equation (4.1)). The problem here is that we do not observe the true input-output coefficients, $a_{ijt}$ (at least in the U.S. data). Or, more accurately, we do "observe" $a_{ijt}$ but only at every 5 years when the BEA constructs input-output tables. Coefficients for years in between are simply interpolated between benchmark-year coefficients. Thus, shocks in q which affect the dependent variable and are part of the regression disturbance term are transmitted to the regressor $(m-\ell)$ causing an upward bias in the estimator of its coefficient.[76]

Therefore, I re-ran the regressions corresponding to 3, 4, 10, and 11 omitting the $\theta(m-\ell)$ term (these new *sans*-materials specifications will hereafter be referred to as 3', 4', 10', and 11'). This can be justified theoretically by assuming that materials and value added have a Leontief relationship as is frequently done in the literature (e.g., Basu (1996) and Wilson (2000)). That is, $Y = min[M, F(J,S,L)]$. Assuming firms are optimizing, this implies $dlog(Y) = dlog(F(J,S,L))$. The $F(\ )$ function can be any of equations (1)-(11) after omitting the term $\theta(m-\ell)$.

Figures 4-10 through 4-17 summarize the results of these regressions (ignore for now the specifications labelled 4" and 11", these will be explained below). As expected, the adjusted $R^2$'s fall, though not by much, when materials are left out (see Figure 4-10). Again the fits are higher when capital utilization is adjusted for. And again specification (11) yields nonsensical average elasticities (though not in the nonmanufacturing subset). The specifications that use the quality-adjusted equipment stocks (3' and 4') yield quite reasonable factor elasticities, particularly the specification

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[11] In fact, exactly the same problem is true for our measures of real energy expenditures which are also constructed via slow-moving input-output coefficients multiplied by industry output.

which does not include the energy-labor ratio (3'). Compared to the (4'), the non-utilization adjusted specification (3') has a somewhat lower percentage of $\eta$'s that are positive but a much higher percentage of positive $\alpha$'s. This result does not appear to be the case in nonmanufacturing though, where (4') dominates (Figure 4-15 and 4-16). In the two equations that include embodied R&D (10' and 11'), the average $\sigma$, over all sectors, is realistic when I do not adjust for utilization and quite unrealistic when I do. When utilization is not adjusted for, there is also strong evidence that including embodied R&D causes the coefficients on unadjusted equipment to turn negative, particularly in nonmanufacturing.

Though not in the nonmanufacturing subset, the average estimated elasticities for specification 3' over all sectors are almost exactly as one would expect. The generally accepted estimates of labor and capital's share in the economy's output is 2/3 and 1/3, respectively, when output is value added and 1/3 and 1/6 when output is gross output (with materials responsible for the other ½). The capital share is further broken down, generally, to be 2/3's equipment (which includes embodied R&D) and 1/3 structures. Thus, one would expect our estimates of the output elasticities with respect to each input to be somewhat close to these values. This means that when materials are included, we would expect $\alpha(+\sigma) \approx (1/6)*(2/3)=2/18 = 0.111$, $\eta \approx (1/6)*(1/3)=1/18 = 0.056$, $\beta = 0.33$ and $\Theta \approx 0.5$. When materials are excluded, we expect $\alpha(+\sigma) \approx 2/9 = 0.222$, $\eta \approx 1/9 = 0.111$, and $\beta = 0.66$. According to the average estimates obtained thus far, these *a priori* expectations are met more closely by the regressions which do <u>not</u> include materials.

Overall, as in the previous section where materials were included, specifications 3' and 4' seem to outperform 10' and 11' here. However, before abandoning the idea of including embodied R&D as a separate regressor, I will explore another method of adjusting for utilization applied to both the embodied R&D specification (10') and the specification which uses quality-adjusted equipment stock (3').

C. *Alternative Adjustment for Unobserved Variation in Capacity Utilization*

Besides using the energy-capital ratio, another method that has been suggested to control for unadjusted variation in factor utilization is what is actually used in the current IDLIFT equation. Industry-level variation in utilization is captured by including the terms *qup* and *qdown* which are defined in equation 4.5. The method first measures capacity with the previous peak level of industry output less some “depreciation.” The absolute value of the percentage difference between current output and capacity is then included as a regressor, with positive and negative differences treated asymmetrically. The rationale behind this method is that when current output is being stretched beyond the previous peak level, the economy will be pushing up against capacity constraints, and when output is much below the previous peak, there is excess capacity not being utilized.

There is the possibility, however, of reverse causation (i.e. simultaneity, or what Almon (1998) refers to as the “umbrella effect”[77]) here since industry-level (log) output

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[12] Almon (1998) cautions against the use of “umbrella” variables, which in econometric parlance are simply endogenous variables, as explanatory variables. The name comes from the analogy to using “the number of people carrying umbrellas to explain rainfall.” (p. 97).

is part of both the dependent variable and the regressors *qup* and *qdown*. If there is any measurement error in output, this may bias the coefficients on *qup* and *qdown* as well as artificially inflate the $R^2$'s. This possibility is explored using a mixed empirical-Monte Carlo technique in the next subsection. For now, as an alternative to specifications 4 and 11, I estimate two analogous equations that are simply specifications 3' and 10' with *qup* and *qdown* as additional independent variables. Call these specifications 4" and 11".

The results of these estimations are shown in Figures 4-10 through 4-13 for all sectors and Figures 4-14 through 4-17 for the nonmanufacturing subset. Compared to their energy-intensity counterparts (4' and 11'), specifications 4" and 11" have slightly lower fits but far more reasonable capital elasticities. Compared to their counterparts that do not adjust for variation in utilization (3' and 10'), these equations are quite similar in fit and in the capital elasticities (with the exception of 11" which actually has much more reasonable capital elasticities than 10').

At this point, it seems reasonable to drop from our consideration the specifications which attempt to adjust for unobserved variations in capital utilization using the energy-capital ratios (specifications 4' and 11') due to their propensity to yield nonsensical capital elasticities and to the fact that including *qup* and *qdown* as explanatory variables seems to be a powerful alternative way of adjusting for utilization. I will also drop the specifications which include embodied R&D and an unadjusted equipment stock as separate explanatory variables (specifications 10' and 11"). The rationale behind these specifications was that including embodied R&D separately may be superior in nonmanufacturing industries to using the imputed rates of embodied technological change to compute equipment capital. However, these specifications seem to actually perform much worse in the nonmanufacturing subset than they do overall. Therefore, hereafter I will consider only specifications 3', 4", and 5.

*D. Allowing for Disembodied Technological Change*

It is possible that there is some spurious positive correlations between labor productivity and the factor inputs due to the fact that these variables are all trended upward. In other words, the above equations should probably also contain a Hicks-neutral productivity (or disembodied technology) term that is sure to be highly trended. Therefore, I re-estimated equations 3' and 4" with a single linear time trend added.

The adjusted $R^{2}$'s for both of these specifications are now slightly better than that of the current IDLIFT equation (specification 5) at 0.866, 0.867 and 0.853 for specifications 3', 4", and 5, respectively. The average estimated capital elasticities decrease somewhat due to the introduction of the time trend though they are still quite reasonable. For specification 3', the average $\alpha$ falls from 0.22 absent the time trend to 0.01 with it, while the average $\eta$ rises from 0.15 to 0.17. Similarly, the percentage of $\alpha$'s that are positive falls from 80% to 52% and the percentage of $\eta$'s that are positive rises from 52% to 63%. For specification 4", $\alpha$ falls from 0.22 to 0.08 on average with the inclusion of the time trend and the average $\eta$ remains at 0.18. The positivity of $\alpha$ falls from 80% to 59% and that of $\eta$ drops from 61% to 57%. The results are quite similar in the nonmanufacturing subset.

From the results of this round of regressions, the most promising specification appears to be 4" with a time trend. 3' with a time trend also seems to be reasonable, though the average equipment elasticity is probably too low and the equipment elasticity is somewhat less likely to be positive under 3' relative to 4". Compared to the former IDLIFT equation, these specifications have as good a fit and obviously have far more economic appeal. Most importantly, they capture the productivity gains due to capital deepening (which, given how capital was constructed here, includes embodied technological change). Therefore, one of these two specifications, along with the coefficients found from estimating them, are used for each of the 55 sectors and can now be incorporated into the IDLIFT model. For a particular industry, which specification is used is chosen on a case-by-case basis based on the criterion of best fit and most realistic coefficients. For the sake of clarity, let us explicitly write out specification 3':

$$q - \ell = c^0 + c^1 t + \alpha(j - \ell) + \eta(s - \ell) \tag{4-8}$$

and specification 4":

$$q - \ell = c^0 + c^1 t + \alpha(j - \ell) + \eta(s - \ell) + b^0 qup + b^1 qdown \tag{4-9}$$

*E. Mixed Empirical-Monte Carlo Test for Bias*

As mentioned above, the fact that *qup* and *qdown* are constructed using q which is also part of the dependent variable for the above regressions, means that if there is measurement error in q, the coefficients on *qup* and *qdown* will be biased. This can be seen formally by assuming that there is an i.i.d. measurement error in q: $q^{true} = q^{measured} + \nu$, where $\nu \sim N(0, 2.5\times10^{-04})$. This says that the standard deviation in the measurement error of log output is assumed to be one half of one percent, which should be as large as is realistically possible. So our regression equation (4-9) becomes:

$$(q^{measured} - \ell)_t = c^0 + c^1 t + \alpha(j - \ell)_t + \eta(s - \ell)_t$$
$$+ b^0 qup_t^{measured} + b^1 qdown_t^{measured} + u_t$$

Notice that $\nu$ will be contained in the dependent variable as well as qup and qdown resulting in spurious correlation between these two regressors and the dependent variable. The bias on the estimator of $b^0$ will be positive and that of $b^1$ will be negative. To evaluate the seriousness of this problem, I perform a mixed empirical-Monte Carlo estimation procedure. In this procedure, I specify the data generating process (DGP) for the true dependent variable as:

$$(q - \ell)_t^{true} = 2 + 0.01 * t + 0.17 * (j - \ell)_t + 0.16 * (s - \ell)_t$$
$$+ 0.1 * qup_t^{true} - 0.1 * qdown_t^{true} + \varepsilon_t$$

where $\epsilon_t \sim N(0, 4\times10^{-06})$, so that the standard deviation of the i.i.d. shock to true productivity is 0.002. The 0.01 and -0.01 assumed coefficients represent the true relationship between qup and qdown and labor productivity, i.e. absent any spurious correlation due to the presence of measurement error in q. Using this DGP, I construct this "true" dependent variable, then regress it on $t$, $(j\text{-}\ell)$, $(s\text{-}\ell)$, $qup^{measured}$, and $qdown^{measured}$ each measured with actual historical time series. I repeat this procedure 2000 times and calculate the mean and standard deviation for each coefficient.[78]

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[13] I arbitrarily choose the "Printing and Publishing" industry for the historical data. The choice of industry should not affect the coefficient means (and therefore their biases) but may affect the standard deviations since the sample variance of a variable helps determine the variance of its coefficient (and, of course, the sample variance of a variable will be different across industries). To be sure, I repeated the procedure with a 2nd industry and obtained similar estimated biases.

The coefficient means and standard deviations are shown in Table 4.2.

**Table 4.2 Mixed Empirical-Monte Carlo Results**

| Coefficient | True value | Mean Estimate | Std. Deviation | Estimated Bias |
|---|---|---|---|---|
| $c^0$ | 2 | 1.99092 | 0.23680 | -0.00908 |
| $c^1$ | 0.01 | 0.00968 | 0.00842 | -0.00032 |
| $\alpha$ | 0.17 | 0.18120 | 0.28050 | 0.0112 |
| $\eta$ | 0.16 | 0.15852 | 0.03292 | -0.00148 |
| $b^0$ | 0.1 | 0.10118 | 0.35719 | 0.00118 |
| $b^1$ | -0.1 | -0.08530 | 0.37322 | 0.0147 |

The estimated biases are all extremely close to zero. Thus, even assuming a very large variance for the measurement error in q, coefficient bias due to the presence of *qup* and *qdown* does not appear to be a problem.

## 6. Conclusion

The main result of this chapter is that a Neoclassical labor productivity equation does exist that can successfully fit the industry-level time-series data and yields realistic coefficient estimates. Careful attention was paid to the correct measurement of the equipment capital stock used to estimate this equation. A physical depreciation pattern was used that closely matches the average physical depreciation schedule suggested by Federal Reserve capital stock data. This pattern was used in conjunction with the rates of embodied technological change that were found in Chapters 2 and 3 of this dissertation. A series of industry-level labor productivity regressions were run according to many different specifications. The results confirmed that accounting for embodied technological change in the equipment capital stock measures greatly aids in the fit and economic realism of the fitted equations. I also found that controlling for unobserved variations in capacity utilization in the same manner as was done in the former IDLIFT equations yields a modest improvement along these dimensions. Counter-historical simulations can now be run with both the former IDLIFT labor productivity equation as well as equation (4-7). The results of these two counter-historical simulations can be used to determine the effect that changing the labor productivity equations has on the macroeconomic variables forecasted by the model.

Chapter 5

**Building the New IDLIFT and Evaluating the Changes**

## 1. Introduction

The general-to-specific modeling approach of the previous chapter allowed us to narrow our search for one or more specifications for industry-level labor productivity equations. In Section 2 of this chapter I describe the process by which the best single *equation* (i.e. specification plus estimated coefficients) was determined for each industry. These equations are incorporated into IDLIFT through a series of new C++ routines which take forecasted values of equipment investment, structures investment, and output and generate values for productivity, hours, and employment, which then get fed back into the model. These routines are described in Section 3 and Appendix C. In Section 4, I run both the new model and the old model in order to produce base forecasts out to 2015.[79] I then compare the models' responses to permanent and temporary shocks in equipment investment. Section 5 concludes.

## 2. Determining Industry-Specific Labor Productivity Equations

In the previous chapter, we evaluated many possible specifications for a general empirical model of labor productivity based on the criteria of average fit and the economic realism of the coefficients. The results of that evaluation have enabled us to

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[1] The model using the new, alternative productivity equations will be referred to as the "new" model in this chapter while the old/current/pre-existing IDLIFT model will be referred to as the "old" model.

now focus our attention on a small number of specifications in determining the “best” one for each particular industry (rather than simply the best on average). Obviously, the specification that yields the best results on average may not necessarily yield the best results for a particular industry. The choice of specification must be made on an industry-by-industry basis.

For each industry, I compare the results of estimating specifications 3', 4'', and 5 (see Chapter 4 for the equation forms). For a small number of industries, it was clear that the lagged values of the equipment and structures stocks had more explanatory power (with reasonable coefficients) than the current values and, thus, the lagged stocks were used instead. The improved explanatory power afforded by using lagged stocks can be explained by the industry having a time-to-build requirement greater than one year and/or by the presence of substantial learning-by-doing effects. For most industries, even the best specification yielded one or more unrealistic coefficients. For these industries it was necessary to “softly constrain” the coefficient estimates to lie inside a realistic range. “Soft constraining,” also known as “Theil’s mixed estimation” or “stochastic constraints,” is a Bayesian regression technique that allows one to combine *a priori* theoretical beliefs on parameter values with the values estimated using the data. A soft constraint essentially adds artificial observations (or a fraction of an observation) in which the constraint holds with certainty. The *a priori* expectation for parameter values and the number of artificial observation to add are chosen by the econometrician. I only imposed soft constraints if the unconstrained estimated coefficient was outside the range of [0,0.4] for either capital elasticity, [0,1] for the coefficient on *qup*, and [0,-1] for the coefficient on *qdown*. The theoretically-based, *a* *priori* expected parameter values that I used as soft constraints were 0.18 for the elasticity of output with respect to the equipment stock, 0.17 for the structures elasticity, 0.5 for the coefficient on *qup*, and -0.5 for the coefficient on *qdown*.[80]

Table 5-1 shows the number of industries for which each of the four specifications was chosen (second column) as well as the number, within each specification, that required soft constraining (third column). Recall that the regressors in specification 3' are a constant, time trend, log of the equipment-labor ratio, and the log of the structures-labor ratio. Specification 4" includes these same regressors in addition to *qup* and *qdown*. Specification 5 is the traditional (current) IDLIFT labor productivity equation. Let the specification which is equivalent to specification 3' but with lagged capital stocks be denoted specification 12.

**Table 5-1 Specification Choice**

| Specification | Number of industries | Number requiring soft constraints |
|---|---|---|
| 3' | 19 | 18 |
| 4" | 27 | 25 |
| 5 | 4 | 2 |
| 12 | 4 | 4 |
| Total | 54 | 49 |

Specification 4" was chosen in exactly one half of the industries. Overall, all but five industries required some type of soft constraint(s). In nearly all cases, the soft

[2] The rationale behind these *a priori* values for capital elasticities is explained in Chapter 4, Section 5B. The *a priori* values for the coefficients on *qup* and *qdown* were chosen simply to be at the halfway point of their respective plausible ranges.

constraints were quite weak, amounting to only a fraction of an artificial observation. Thus, the equation fits suffered very little due to the use of soft constraints.

## 3. Incorporating the Alternative Estimated Equations into IDLIFT

Incorporating these new labor productivity equations into the IDLIFT model turned out to far more complicated than it would seem at first. The task at hand was to use the new labor productivity equations to determine productivity and employment, at the 97-sector level of aggregation, which can feed back into the model. The model can then use the productivity and employment forecasts to help calculate various other components of the model such as the unemployment rate and hourly labor compensation.

The first complication was how to deal with having labor hours, which are calculated *using* the productivity equations, on the right-hand side of the productivity equations. There are at least three options for handling this problem. The first is to algebraically rearrange each of the specifications containing hours on the right-hand side so that output is on the right-hand side instead and then estimate the equations in this form. For example, specification 3' can be rearranged from:

$$q - \ell = c^0 + c^1 t + \alpha(j - \ell) + \eta(s - \ell) \tag{5.1}$$

to:

$$q - \ell = \left(\frac{1}{1-\alpha-\eta}\right)\left\{c_0 + c_1 t + \alpha j + \eta s - (\alpha+\eta)q\right\} \tag{5.2}$$

I tried this approach and found that the capital elasticities implied by the estimated coefficients were far less sensible than those estimated directly in Chapter 4. As in Section 2 above, one could impose soft constraints to force the coefficients into a range that would imply reasonable capital elasticities. However, the constraints would have to be much stronger, i.e., the trade-off between *a priori* expectations of parameter values and those estimated by the data would have to lean far more towards the former. Another option would be to program the equations into the model with hours on the right-hand side, supply the model with starting values (a guess) for hours, let the productivity equations calculate new values for hours, and then let the model iterate until it converges. The third option is to use the estimated equation coefficients found in Section 2 above, but use them in the algebraically rearranged forms of the specifications (such as (5.2) above) which have output on the right-hand side. This option requires no iterative procedure since output has already been calculated earlier in the model and thus this is the option I used.

The next issue that needed to be dealt with was how to get forecasted values of structures investment at the 55-industry level, the level of disaggregation at which the productivity equations were estimated. Previously, the IDLIFT model generated only *equipment* investment by 55 industry and structures investment by *type*. The 25 types/categories of construction are listed in Appendix D. Rather than developing new structures investment equations by industry, similar to the equipment investment equations, I instead exploited the fact that there is (approximately) a clear one-to-many mapping from some construction types to the industries that purchase those types. For instance, construction of “Farm buildings” (construction type 13) can be clearly attributed to the “Agriculture, forestry, and fisheries” investment industry (industry 1). This assumption can be supplied exogenously to the model through what is known as a “fix.” Fixes are supplied by the model user and override or modify the equation results of endogenous variables. Thus, I fix structures investment in industry 1 to "follow" construction of farm buildings, starting from the last year of historical data for structures investment by industry (1997). That is, structures investment in year t, $S_t$, is determined by equalizing $S_t/S_{1997}$ to $C_t/C_{1997}$ for all t>1997, where C is construction in the corresponding type. Similarly, for cases where one type is associated with many industries, such as "Industrial" construction which is attributable to all of the manufacturing industries, I fix structures investment in each industry to follow the model's forecast for construction in that type. Again, industry structures investment does not *equal* the value of construction in that type; rather, it starts with the last historical data point and then moves forward at the same ratio of forecast year value to last data value that is the case in the forecasts of construction by type. For two industries (which each have very little investment in structures anyway), no clear match could be made to a construction type and so structures investment in those industries was assumed to simply follow aggregate nonresidential construction from their last data point on.[81]

Now, with forecast values for structures and equipment investment by 55 industry, one can calculate structures and quality-adjusted equipment capital stocks to be used in the productivity equations. This is done in the C++ routine, DANBKT.CPP, which is shown in Appendix C along with the other new routines. The routine takes in forecasted values of structures and equipment investment along with the exogenously supplied rates of embodied technological change and produces stocks. The stocks of structures are calculated using the traditional perpetual inventory method with

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[3] The two industries are Construction (6) and Air transportation (40).

depreciation rates computed as the reciprocal of the mean service life of structures in that industry (provided by the BEA). The quality-adjusted equipment capital stocks are calculated using the estimated rates of embodied technological change and the cascading bucket system described in Section 4 of Chapter 4.

The routine DANPROD.CPP then takes in these stocks along with the model's forecasted values of output by 55 industries (which are aggregated from the 97-sector level) and the coefficient estimates for the productivity equations (including the estimate of $\rho$, the autocorrelation coefficient) and calculates both productivity and hours for each industry. Since other stages of the model require productivity and hours at the 97-sector level, these had to be disaggregated to that level. To split 55-industry hours to the 97-sector level, I used a one-to many mapping key. The shares used to split one industry to many sectors were taken from the 97-by-1 hours vector forecasted by the old IDLIFT productivity equations. Thus, the old productivity equations were left operational in the model solely for the purpose of providing time-varying shares for this disaggregation. Productivity at the 97-sector level was then calculated by simply dividing the output (already generated by the model at this level) by the 97-sector level hours. Employment at the 97-sector level was calculated by dividing hours by the model's forecasts of average annual hours per worker. The disaggregation and the calculation of productivity and employment can be seen in the routine REMPLOY.CPP in Appendix C.

## 4. Forecast and Simulation Results

With these new, alternative routines incorporated into the model (along with the estimates for the productivity equations), one can produce a base forecast that is stable, i.e. a forecast that does not cause any variable to spiral out of control. In addition, these new routines were programmed into the model in such a way as to allow the model to calculate productivity, hours, and employment using both the new set of equations and the old set of equations. The model user can specify which set of equations he or she would like to feed back into the model. That is, the user can have the model calculate productivity and hours using the new equations but have those calculated values in no way affect the rest of the model, and the same for the old equations. This allows one to generate a base forecast for both the current model (i.e. the model set to have the old equations' forecasts feed back into the model) and the new model (having the new equations feed back into the model).

Since what we are interested in is how the behavior of the two models differs in response to changes in economic activity, such as variations in equipment investment, comparing the two base forecasts to one another is of little interest. What will be of interest to us in this section is comparing and contrasting the responses of each model to some exogenous shock to the system. The behavior of each model in response to such an experiment is the only way to illuminate the effect of changing the IDLIFT's productivity equations. Since the key difference between the two models is the presence of a direct influence of capital stock on productivity in the new model, the interesting shocks to investigate will naturally involve investment.

Moreover, given IDLIFT's dependence on many exogenous, user-supplied assumptions ("fixes"), one cannot fairly compare a forecast from the old model with one from the new model. The existing fixes, which either override or modify the endogenous forecasts produced by the model's equations, were specified in such a way as to produce the most sensible forecast using the *current* model. Alternatively, these fixes could be specified so as to optimize the sensibility of the new model. However, having each model have its own optimal fixes would confuse the differences in the models' results due to different productivity equations with those due to different sets of fixes. Yet, many of these fixes must be given values for the model to run at all, therefore turning off all fixes is not an option either. Thus, I run both models using the fixes in place for the most recent semi-annual Inforum forecast using IDLIFT (see Inforum (2001)). One important exception is the exclusion of all fixes on industry-level productivity, industry-level employment, and the aggregate unemployment rate. Thus, again, comparison of the two models must be between the models' *differences* from their own base forecast to a simulation forecast in which a shock was imposed, and not between the models' base forecasts.

To produce base forecasts, I ran each model out to 2015. 1997 was the last year of historical data for most of the industry-level variables in the model, yet much of the aggregate data is available through 2000 (or at least through 1998 or 1999) and this data is imposed on the model through fixes (with the exception of the unemployment rate as mentioned above).[82] The new functions generally result in lower labor productivity and thus higher hours and employment in the base forecast. This result is true even if the output of these functions is not fed back into the model, but it is stronger when feedback does occur. However, this difference in productivity between

[4] For instance, NIPA data is available on aggregate equipment investment and residential and nonresidential structures through 2000.

the base forecasts is largely due to fixes that act to boost productivity in the current model and thus is not very interesting.

For each model, I then evaluate the response of the model to a shock in equipment investment. Specifically, with a set of fixes on equipment investment, I override the models' forecasted vectors of equipment investment with the investment vector from the base forecast plus 2%. That is, for each industry I multiply the equipment investment values from the base forecast by 1.02 and force the model to use these new values in all of the functions that make use of equipment investment. Because aggregate equipment investment is known (from NIPA data) through 2000, I impose this fix for the years 2001 through 2015.

Figures 5-1 through 5-10 graph, for each model, the deviations over the forecast period of key macro variables relative to each model's base forecast. In both models, real GDP rises by about a quarter of a percent relative to the base in the first year in which the 2% higher equipment investment is imposed. From then on the models diverge substantially. The old model falls to near the base level in the second year, oscillates between 0.05% and 0.2% over base through 2008, then seems to settle at about 0.08% over base. The new model also comes back down closer to base in 2002 but then rises relative to base almost monotonically until the end of the forecast where it stands at 0.31% over base. This Solowian response of real GDP, i.e. higher and less variable, to permanently higher equipment investment is what one would have expected and hoped for from the new model. The increase in labor productivity induced by higher investment also reduces unit labor costs and this reduction lowers the GDP deflator. The GDP deflator rises in the old model in response to the demand stimulus of higher investment. Because of this, the deviation from base in *nominal* GDP is actually higher in the old model. The different responses of the price level also has an effect on the Treasury bill rate: the deviation from base is generally lower and less volatile in the new model. The lower interest rates in the new model cause, in part, a smaller deviation in the savings rate.

In both models, the unemployment rate goes down relative to base due to the substantial demand stimulus caused by the increase in investment. However, the deviation is smaller on average in the new model because its increase in labor productivity has an immediate negative effect on employment. This Ricardian (or Luddite) effect would have occurred in the old model as well had labor productivity increased substantially, which it did not.[83] This difference in labor productivity deviations can be seen in Figure 5-10. Labor productivity in the new model grows steadily to almost 0.4% above its base level by the end of the forecast. This is compared to the old model in which productivity oscillates until it converges to about 0.04% over base. In short, in the new model, the effect of investment on productivity is ten times what it was in the old model.

The deviations in labor productivity by industry for the new model are shown in Table 5-2 below, along with each industry's estimated elasticity of output with respect to equipment capital stock. As one would expect, the largest deviations can be found in

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[5] In Ricardo's later works, he developed the notion that the introduction of machinery can, under certain circumstances such as the sudden introduction of a new type of machinery, have an adverse effect on employment. In his *Notes* to Malthus's *Principles*, he states:

> It might be possible to do almost all the work performed by men with horses, would the substitution of horses in such case, even if attended with a greater produce, be advantageous to the working classes, would it not on the contrary very materially diminish the demand for labor?

industries which have the largest elasticities of equipment stock. The correlation between this elasticity and the deviation in labor productivity is approximately zero in 2001 but rises to 0.96 by 2015.

## Table 5-2 Deviations in Labor Productivity (Permanent Shock)

| Industry | Equipment Elasticity | 2001 | 2005 | 2010 | 2015 |
|---|---|---|---|---|---|
| | | Percent Deviations from Base | | | |
| 1 Agriculture, forestry and fisheries (3’) | 0.288 | 0.02 | 0.54 | 0.83 | 0.97 |
| 2 Metal mining (12) | 0.094 | -0.30 | -0.09 | 0.00 | 0.03 |
| 3 Coal mining (3’) | 0.295 | -0.05 | 0.52 | 0.87 | 1.05 |
| 4 Crude petroleum and natural gas (3’) | 0.359 | -0.04 | 0.69 | 1.05 | 1.21 |
| 5 Non-metallic mining (4") | 0.065 | 0.02 | 0.06 | 0.10 | 0.12 |
| 6 Construction (4") | 0.318 | 0.08 | 0.56 | 0.87 | 1.02 |
| 7 Food and tobacco products (4") | 0.206 | 0.06 | 0.32 | 0.48 | 0.57 |
| 8 Textile mill products (4") | 0.060 | 0.09 | 0.08 | 0.13 | 0.14 |
| 9 Apparel and other textile products (4") | 0.131 | 0.02 | 0.13 | 0.22 | 0.28 |
| 10 Paper and allied products (4") | 0.133 | 0.09 | 0.11 | 0.21 | 0.27 |
| 11 Printing and publishing (4") | 0.140 | 0.22 | 0.09 | 0.17 | 0.22 |
| 12 Chemicals (12) | 0.239 | -0.12 | 0.34 | 0.63 | 0.76 |
| 13 Plastics and synthetic materials (12) | 0.207 | -0.20 | 0.18 | 0.44 | 0.54 |
| 14 Petroleum refining (4") | 0.025 | 0.03 | 0.01 | 0.03 | 0.05 |
| 15 Rubber and miscellaneous plastics (4") | 0.081 | 0.31 | 0.08 | 0.13 | 0.14 |
| 16 Footwear and leather products (3’) | 0.326 | 0.03 | 0.35 | 0.63 | 0.79 |
| 17 Lumber and wood products (3’) | 0.054 | -0.04 | 0.06 | 0.12 | 0.12 |
| 18 Furniture (4") | 0.026 | 0.36 | -0.04 | -0.03 | -0.02 |
| 19 Stone, clay and glass products (4") | 0.058 | 0.05 | 0.06 | 0.11 | 0.14 |
| 20 Primary iron and steel (4") | 0.095 | 0.16 | 0.09 | 0.15 | 0.16 |
| 21 Primary nonferrous metals mfg. (4") | 0.055 | 0.17 | 0.06 | 0.09 | 0.10 |
| 22 Metal products (4") | 0.064 | 0.15 | 0.05 | 0.09 | 0.11 |
| 23 Engines and turbines (3’) | 0.123 | -0.16 | 0.04 | 0.13 | 0.16 |
| 24 Agricultural, construction & mining mach. (3’) | 0.061 | -0.18 | -0.11 | -0.07 | -0.06 |
| 25 Metalworking machinery (5) | N/A | 0.56 | 0.00 | 0.00 | 0.01 |
| 26 Special industry machinery (5) | N/A | 0.15 | 0.01 | 0.00 | 0.02 |
| 27 General and miscellaneous industrial mach. (3’) | 0.062 | -0.19 | -0.07 | -0.01 | 0.03 |
| 28 Computers and office equipment (3’) | 0.125 | -0.23 | -0.04 | 0.04 | 0.08 |
| 29 Service industry machinery (4") | 0.083 | 0.43 | 0.08 | 0.11 | 0.12 |
| 30 Electrical industrial equipment and app. (4") | 0.088 | 0.40 | 0.03 | 0.08 | 0.10 |
| 31 Household appl., elec lighting & wiring (4") | 0.306 | 0.29 | 0.48 | 0.72 | 0.81 |
| 32 Audio, video and comm. equipment (3’) | 0.073 | -0.17 | -0.06 | 0.00 | 0.03 |
| 33 Electronic components (4") | 0.215 | 0.01 | 0.32 | 0.45 | 0.49 |
| 34 Motor vehicles and equipment (3’) | 0.086 | -0.12 | 0.02 | 0.10 | 0.12 |
| 35 Aircraft and parts (3’) | 0.195 | 0.00 | 0.25 | 0.37 | 0.40 |

| | | | | | |
|---|---|---|---|---|---|
| 36 Ships and other transportation equipment (4") | 0.074 | -0.03 | 0.02 | 0.05 | 0.06 |
| 37 Instruments (3’) | 0.158 | -0.07 | 0.12 | 0.22 | 0.26 |
| 38 Miscellaneous manufacturing (4") | 0.297 | 0.06 | 0.44 | 0.61 | 0.65 |
| 39 Railroad transportation (12) | 0.029 | -0.08 | -0.04 | -0.02 | -0.01 |
| 40 Air transportation (3’) | 0.330 | 0.11 | 0.82 | 1.09 | 1.16 |
| 41 Trucking and other transport (3’) | 0.094 | -0.07 | 0.05 | 0.11 | 0.13 |
| 42 Communications services (3’) | 0.183 | -0.02 | 0.37 | 0.48 | 0.50 |
| 43 Electric utilities (3’) | 0.349 | 0.08 | 0.66 | 0.93 | 1.02 |
| 44 Gas, water and sanitary services (3’) | 0.095 | -0.07 | 0.05 | 0.09 | 0.11 |
| 45 Wholesale trade (4") | 0.089 | 0.10 | -0.05 | 0.03 | 0.06 |
| 46 Retail trade, restaurants & bars (5) | N/A | 0.02 | 0.00 | 0.00 | 0.00 |
| 47 Finance and insurance (4") | 0.036 | 0.04 | 0.02 | 0.01 | 0.03 |
| 48 Real estate and rental (5) | N/A | 0.04 | 0.00 | 0.00 | 0.00 |
| 49 Hotels, repairs except auto (4") | 0.132 | 0.11 | 0.14 | 0.20 | 0.22 |
| 50 Business and professional services (4") | 0.214 | 0.15 | 0.08 | 0.25 | 0.32 |
| 51 Automotive repair and services (4") | 0.031 | 0.11 | 0.01 | 0.04 | 0.06 |
| 52 Movies and amusements (4") | 0.161 | 0.14 | 0.23 | 0.31 | 0.34 |
| 53 Health services (3’) | 0.348 | 0.17 | 0.71 | 0.92 | 0.98 |
| 54 Educational and social services and NPO (3’) | 0.147 | 0.01 | 0.23 | 0.29 | 0.31 |

Next I impose a one-time shock on each model of 10% higher equipment investment (relative to that which is forecast by the model’s equations) in 2001. Determination of equipment investment returns to IDLIFT’s investment equations from 2002 on. The shock is assumed to take place in every industry. Figures 5-11 through 5-21 show the deviations relative to the base for the same macro variables as in the earlier figures as well as equipment investment (Figure 5-21) and quality-adjusted equipment stock (Figure 5-22).[84] Both models have an initial response of between 1.2 and 1.3 percent in real GDP. After oscillating for several years, the old model returns nearly to its base level. The new model, however, quickly reaches a steady state at approximately three-tenths of a percent above its base. As with the previous

[6] Equipment investment here is not adjusted for embodied technological change. Also, note that though quality-adjusted equipment capital is shown for both models in Figure 5-22, it only has an effect on the other variables (as well as its own future values through the investment equations) in the new model.

experiment, the GDP deflator's deviation is lower in the new model than in the old model. The GDP deflator converges to the base level over time in the old model whereas it falls steadily relative to the base in the new model. Interest rates deviations move similarly in the two models though they are somewhat less volatile in the new model. The same is true for their savings and unemployment rates. In both models, unemployment initially drops dramatically in response to the shock, then jumps dramatically, and finally begins to converge to its base level around 2005. The new model has less of a drop and subsequent jump because the positive demand stimulus of raising investment is partially offset by the increase in productivity which has a negative effect on employment in the short-run (the Ricardian effect), though this is dominated by the stimulus as can be seen in Figure 5-17.

As expected, labor productivity in the old model, after oscillating for several periods, returns to its base level by 2010 and stays there whereas productivity in the new model, after also oscillating for a few years, is permanently above its base levels. This permanent increase in productivity in response to a temporary increase in investment is the key difference in the behavior of the two models. In the old model, a one-time jump in aggregate investment only affects labor productivity by directly increasing every industry's final demand, which directly increases their output, which increases their *qup* which increases their labor productivity. The next year, when equipment investment comes back down, output will likely be below its previous peak making *qdown* go up which will lower labor productivity. This cycle will fade away over time returning labor productivity to its base level. In the new model, on the other hand, labor productivity in every industry jumps initially because of both the jump in *qup* and the jump in the equipment stock. In the following year, productivity comes back down due to the jump in *qdown* in the following period but this decline is offset somewhat by the still-present higher level of equipment stock. There is also a strong and long-lasting positive effect on equipment investment itself from the initial shock. This effect has two causes. First, the 2001 jump in investment causes the following year's desired capital stock (constructed and used in the model's investment equations) to rise which increases the forecast of investment for that year which then increases desired capital and investment for the next year, and so on. Furthermore, the increase in final demand in 2001 raises the 2000-01 change in output. Distributed lags in the change in output are part of the model's investment equations. Thus, the increased change in output in 2001 directly increases investment for the following four years (there are four lags of output change in the investment equations).

The continuing though depreciating presence of that extra 10% of equipment purchased in 2001, combined with the long-lasting increase in equipment investment due to the positive feedback from the initial demand stimulus, keeps the quality-adjusted equipment stock about 2% above its base level from 2005 through the end of the forecast (see Figure 5-22). The physical depreciation and obsolescence of the extra 10% of vintage-2001 equipment begins to dominate any positive feedback remaining from the initial stimulus by 2009 and a very slow decline in the equipment stock begins. Shortly thereafter, labor productivity thus begins to decline very slowly.

The labor productivity deviations from the base forecast of the new model are shown for each industry in Table 5-3 below, along with each industry's estimated elasticity of output with respect to equipment capital. As was the case with the permanent shock, the largest deviations are in industries with large elasticities of equipment stock. The correlation between the estimated elasticity and the deviation in productivity is -0.07 in 2001 but rises to 0.82 by 2015.

## Table 5-3 Deviations in Labor Productivity (One-Time Shock)

| Industry | Equipment Elasticity | Percent Deviations from Base 2001 | 2005 | 2010 | 2015 |
|---|---|---|---|---|---|
| 1 Agriculture, forestry and fisheries (3’) | 0.288 | 0.32 | 0.74 | 0.97 | 0.96 |
| 2 Metal mining (12) | 0.094 | -1.46 | -0.02 | 0.06 | 0.08 |
| 3 Coal mining (3’) | 0.295 | -0.15 | 1.07 | 1.49 | 1.63 |
| 4 Crude petroleum and natural gas (3’) | 0.359 | 0.04 | 1.11 | 1.47 | 1.56 |
| 5 Non-metallic mining (4") | 0.065 | 0.08 | 0.20 | 0.16 | 0.16 |
| 6 Construction (4") | 0.318 | 0.45 | 1.12 | 1.32 | 1.37 |
| 7 Food and tobacco products (4") | 0.206 | 0.32 | 0.42 | 0.51 | 0.54 |
| 8 Textile mill products (4") | 0.060 | 0.47 | 0.17 | 0.12 | 0.10 |
| 9 Apparel and other textile products (4") | 0.131 | 0.07 | 0.23 | 0.21 | 0.22 |
| 10 Paper and allied products (4") | 0.133 | 0.42 | 0.17 | 0.22 | 0.22 |
| 11 Printing and publishing (4") | 0.140 | 1.12 | 0.27 | 0.20 | 0.21 |
| 12 Chemicals (12) | 0.239 | -0.56 | 0.55 | 0.63 | 0.61 |
| 13 Plastics and synthetic materials (12) | 0.207 | -1.01 | 0.40 | 0.41 | 0.37 |
| 14 Petroleum refining (4") | 0.025 | 0.12 | 0.02 | 0.02 | 0.04 |
| 15 Rubber and miscellaneous plastics (4") | 0.081 | 1.03 | 0.18 | 0.14 | 0.13 |
| 16 Footwear and leather products (3’) | 0.326 | 0.19 | 0.52 | 0.74 | 0.79 |
| 17 Lumber and wood products (3’) | 0.054 | -0.21 | -0.02 | 0.14 | 0.13 |
| 18 Furniture (4") | 0.026 | 1.83 | 0.16 | -0.01 | -0.01 |
| 19 Stone, clay and glass products (4") | 0.058 | 0.25 | 0.15 | 0.12 | 0.11 |
| 20 Primary iron and steel (4") | 0.095 | 0.79 | 0.20 | 0.17 | 0.16 |
| 21 Primary nonferrous metals mfg. (4") | 0.055 | 0.86 | 0.23 | 0.12 | 0.09 |
| 22 Metal products (4") | 0.064 | 0.78 | 0.16 | 0.11 | 0.11 |
| 23 Engines and turbines (3’) | 0.123 | -0.81 | 0.15 | 0.18 | 0.17 |
| 24 Agricultural, construction & mining mach. (3’) | 0.061 | -0.86 | 0.03 | 0.04 | 0.04 |
| 25 Metalworking machinery (5) | 0.000 | 2.70 | 0.24 | -0.02 | 0.00 |
| 26 Special industry machinery (5) | 0.000 | 0.72 | -0.05 | 0.00 | 0.00 |
| 27 General and miscellaneous industrial mach. (3’) | 0.062 | -0.94 | 0.03 | 0.04 | 0.06 |
| 28 Computers and office equipment (3’) | 0.125 | -1.13 | 0.21 | 0.20 | 0.17 |
| 29 Service industry machinery (4") | 0.083 | 2.16 | 0.29 | 0.16 | 0.15 |
| 30 Electrical industrial equipment and app. (4") | 0.088 | 1.94 | 0.15 | 0.14 | 0.14 |
| 31 Household appl., elec lighting & wiring (4") | 0.306 | 1.30 | 0.87 | 0.80 | 0.77 |
| 32 Audio, video and communication equipment (3’) | 0.073 | -0.85 | 0.04 | 0.06 | 0.06 |
| 33 Electronic components (4") | 0.215 | 0.02 | 0.43 | 0.38 | 0.35 |
| 34 Motor vehicles and equipment (3’) | 0.086 | -0.65 | 0.13 | 0.16 | 0.17 |
| 35 Aircraft and parts (3’) | 0.195 | -0.01 | 0.41 | 0.39 | 0.37 |
| 36 Ships and other transportation equipment (4") | 0.074 | -0.15 | 0.36 | 0.13 | 0.12 |
| 37 Instruments (3’) | 0.158 | -0.36 | 0.31 | 0.32 | 0.31 |

| | | | | | |
|---|---|---|---|---|---|
| 38 Miscellaneous manufacturing (4") | 0.297 | 0.28 | 0.78 | 0.66 | 0.57 |
| 39 Railroad transportation (12) | 0.029 | -0.41 | -0.03 | -0.01 | -0.01 |
| 40 Air transportation (3’) | 0.330 | 0.51 | 1.13 | 1.07 | 0.95 |
| 41 Trucking and other transport (3’) | 0.094 | -0.36 | 0.07 | 0.10 | 0.08 |
| 42 Communications services (3’) | 0.183 | -0.08 | 0.48 | 0.48 | 0.42 |
| 43 Electric utilities (3’) | 0.349 | 0.49 | 1.03 | 1.12 | 1.09 |
| 44 Gas, water and sanitary services (3’) | 0.095 | -0.28 | 0.08 | 0.15 | 0.15 |
| 45 Wholesale trade (4") | 0.089 | 0.02 | 0.08 | 0.09 | 0.09 |
| 46 Retail trade, restaurants & bars (5) | 0.000 | 0.10 | 0.02 | 0.00 | 0.00 |
| 47 Finance and insurance (4") | 0.036 | 0.17 | 0.00 | 0.04 | 0.07 |
| 48 Real estate and rental (5) | 0.000 | 0.20 | 0.00 | 0.00 | 0.00 |
| 49 Hotels, repairs except auto (4") | 0.132 | 0.58 | 0.22 | 0.20 | 0.19 |
| 50 Business and professional services (4") | 0.214 | 2.33 | 1.03 | 0.41 | 0.38 |
| 51 Automotive repair and services (4") | 0.031 | 0.71 | 0.01 | 0.07 | 0.07 |
| 52 Movies and amusements (4") | 0.161 | 0.76 | 0.38 | 0.34 | 0.33 |
| 53 Health services (3’) | 0.348 | 0.93 | 0.92 | 0.96 | 0.87 |
| 54 Educational and social services and NPO (3’) | 0.147 | 0.14 | 0.22 | 0.28 | 0.26 |

## 5. Conclusion

The preceding experiments show that the introduction of the new labor productivity equations into IDLIFT do have substantial effects on the general equilibrium behavior of the model. With the new equations operating, the macroeconomic variables of the model exhibit behavior in response to changes in investment that is more in line with that predicted by the Solow growth model. Importantly, we do not see the model spiral out of control in terms of output or prices when the new equations are introduced as was feared due to the lack of a supply constraint in the investment equations. In general, the macroeconomic situation of the economy is *permanently* and substantially improved by an increase in equipment investment, even if it is only a one-time shock, according to the new model. In contrast, the macroeconomy of the IDLIFT model without the new equations exhibits a smaller long-run benefit due to a permanent investment increase and little or no long-run benefit from a temporary increase. The permanent and reasonable response of the new model to increases in investment was the goal of this dissertation. We now see that using a properly constructed capital stock, one can build a neoclassical labor productivity equation into IDLIFT that allows the model to respond to investment in a way that is consistent with neoclassical economic theory.

# Chapter 6

**Conclusion and Suggestions for Future Research**

## 1. Conclusion

This dissertation sought to bring empirical quantification to bear on an issue which as heretofore remained mainly a theoretical concern: capital-embodied technological change. The theory of embodied technological change and its effects on productivity has a long and illustrious history. Yet, measuring the rate of embodied technological change and the share of total technological change that is embodied is a relatively new endeavor. The delay was likely due to limitations in econometric technique, computational ability, and data availability; lack of concern with measurement issues in general in the economics profession; and a pervasive belief among many economists that mismeasurement of capital is of secondary importance. In recent years, the proper measurement of capital has become of primary concern to empirical economists as rapid technological changes such as the development of computers and related technologies have greatly increased (or at least increased our perception of) the measurement error obtained from traditional methods of measuring capital. In an era in which the generation and use of rapidly evolving technologies in capital is a widely recognized feature of the economic landscape, it is no surprise that the theory and measurement of embodied technological change are receiving renewed attention.

One area in which ignoring embodied technological change can potentially have substantial adverse effects is macroeconomic modeling and forecasting. If we want our macroeconomic models to behave according to neoclassical production theory, we are reliant on proper measures of *productive* capital, that is capital measured in terms of its efficiency as opposed to a measure of the value of capital or the physical quantity of capital. In this dissertation, I built the relationship between investment, embodied technological change, and productivity described by neoclassical theory (augmented by Robert Solow's pioneering work on embodiment) into a pre-existing structural macroeconomic model. In order to quantify this relationship, it was necessary to (1) estimate the rate of embodied technological (a.k.a. quality) change in each of the model's industries, (2) construct historical time-series data on quality-adjusted equipment capital stocks in each industry, and (3) estimate labor productivity equations for each industry using these equipment stocks.

Using a direct, production-side approach, I was able to estimate the rate of embodied technological change in manufacturing industries, albeit with considerable imprecision, by exploiting the cross-sectional variation in intertemporal investment distributions afforded by the large establishment-level Longitudinal Research Database managed by the U.S. Census Bureau. I was able to obtain increased precision by restricting the rate of embodied technological change to be equal across industries. Under this restriction, embodied technological change in the average U.S. manufacturing plant (or at least the average plant in our sample which, it is argued, seems fairly representative of overall manufacturing) is estimated to be approximately 12%, far higher than that suggested by the price-side literature (e.g., Gordon, 1990). This suggests about two-thirds of total technological change in U.S. manufacturing is attributable to embodied technological change.

Unfortunately, such rich data on non-manufacturing establishments does not exist at present.[85] Therefore, a more indirect approach was necessary to get an idea of the rates of embodied technological change in non-manufacturing industries. This approach I developed involved measuring the extent of R&D effort embodied in the capital that an industry uses. Specifically, I gathered data from past National Science Foundation reports listing, *inter alia*, total R&D expenditures applied to various product fields. Many of these product fields are categories of industrial equipment. Combining the R&D by product field data with investment by equipment category data from the Bureau of Economic Analysis, I was able to construct industry-level, time-series indexes of the stock of real R&D spending embodied in an industry's capital stock. The level of R&D stock in a product field was shown to be highly correlated with estimates of the constant-quality price decline in that product field obtained by Gordon (1990). The level of the index of embodied R&D for manufacturing industries was shown to be highly correlated with the estimates of embodied technological change found in the plant-level study. Furthermore, the index of an industry's embodied R&D, averaged over time, relative to other industries was shown to have a positive and significant effect on the industry's relative total factor productivity (TFP) as conventionally measured (i.e. the Solow Residual). This is to be expected if the conventionally measured TFP contains embodied technological change as it will of course if capital does not contain it. Using these indexes of embodied R&D, I imputed rates of embodied technological change for non-manufacturing industries using the

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[1] A non-manufacturing longitudinal database is currently being constructed at the Center for Economic Studies of the U.S. Census Bureau.

relationship between embodied R&D and the rates of embodied technological change estimated in Chapter 2 for manufacturing industries.

Once I had estimates of embodied technological change for all industries, it was a relatively straight-forward endeavor to construct the quality-adjusted equipment capital stocks for each industry. Following a general-to-specific modeling approach, I use these equipment capital stocks, along with other production data, to evaluate various specifications for modeling labor productivity. The goal was to find a specification that was based on neoclassical production theory, fit the data at least as well as the former trend-based specification, and yielded economically sensible coefficients on average. I was able to narrow the search down using this approach and then, in Chapter 5, used a Bayesian "soft constraint" approach on an industry-by-industry basis to settle on a labor productivity equation for each industry. These equations provided the quantitative link between investment, embodied technological change, and productivity which was then incorporated into the IDLIFT structural macroeconomic model.

Having this link in the model greatly enhances its usefulness for policy analyses and simulations while at the same time increasing its economic rationality.[86] With two alternative simulations, I showed that the new model, incorporating this investment-productivity connection, exhibits behavior in response to either a permanent or a one-time equipment investment shock that is more consistent with Solow/Neoclassical growth theory. Many technology-related policy changes can now be simulated using

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[2] See the quote from Almon (1969) in Chapter 4, Section 3 for why missing this link forsakes economic rationality.

the model. The effect of enacting or repealing investment tax credits is an obvious example. Also, policies relating to federal R&D funding, tax incentives for private R&D, patent protection, the supply of scientists and engineers, and many areas are likely to have a direct effect on the rates of embodied technological change. The macroeconomic and industry-level effects of changes in embodied technological progress can now be easily evaluated with this model.

## 2. Suggestions for Future Research

The literature on embodied technological change and its macroeconomic effects is relatively sparse, particularly on the empirical front. This sparseness leaves many areas for future research. One issue that could not be addressed ideally with the current data and econometric methods is the possibility of reverse causation or simultaneity biasing the rates of embodied technological change estimated in Chapter 2. The lack of available time-varying instruments at the plant-level for a sufficiently large number of plants hampered the ability to use the conventional method of obtaining consistency in the face of simultaneity bias: instrumental variables. Simultaneity bias has been receiving increasing attention in recent years and new techniques for handling it are being developed rapidly. Moreover, the value of establishment-level and firm-level data is being recognized now more than ever before and this greatly increases the potential for finding suitable instruments for production function studies.

Another issue that was raised by this dissertation and which remains ripe for further research is the connection between R&D and embodied technological change.

In Chapter 3, I argued (and provided evidence) that the embodied technological change occuring in an industry is determined by (1) the composition of the industry's investment over types of equipment, and (2) the amount of R&D that has been spent over the years by the entire economy on developing those types of equipment. In the process, I constructed a panel data set of R&D by product field and year which can be used for a plethora of research projects. For example, one could study what characteristics of a product affect how much R&D is applied by the economy as a whole on that product. The index of embodied R&D by industry and year may also be quite useful for purposes other than simply imputing rates of embodied technological change. A study of its correlation with and effect on other industry-level variables could be quite illuminating. Furthermore, given data on investment by asset type (available for a small number of years in the Annual Capital Expenditures Survey (ACES)), measures of embodied R&D could also be constructed at the firm-level. These measures may provide an indication of the embodied technological change occuring in a given firm. A much broader and more in-depth analysis could then be done relating embodied technological change (or at least embodied R&D) to other firm-level variables such as wages, labor-skill composition, market value, productivity, etc..

As for the IDLIFT model, there are a number of areas related to the productivity-investment link that can and should be explored in the future. The most pressing is probably developing a set of equations to forecast structures investment by industry. Equations similar to those for equipment investment could be tried out with the totals of certain industries being controlled by the model's forecasts of construction by type (for example, total structures investment by all manufacturing industries could be controlled to “industrial” construction). Another area where future analysis would be useful is the productivity equations in the service industries. The data, particularly the output data, used to estimate these equations is suspect at best and is often simply imputed from labor hours. Alternative data sources could be explored and the equations re-estimated for these industries. Most pressing is the equation for retail trade. Retail trade accounts for almost as large a share of total employment as all of the manufacturing industries combined. Yet, the productivity equation for this industry remains one based on time trends and the difference in output from its previous peak because a specification containing capital did not fit the data well at all.

A more substantial project would be to work on introducing a supply constraint into the investment equations (or perhaps elsewhere in the model). A supply constraint, such as a non-convex adjustment cost, could prevent the model from spiralling out of control in terms of output in very long forecasts. With investment directly increasing productivity, there is the potential (which will be even greater if and when retail trade’s productivity becomes linked to investment) for a demand stimulus to have the effect of increasing output, which increases investment, which increases productivity, which increases wages, which increases consumption, which increases output, and so on in a virtuous circle until output is unrealistically high in some or all sectors. A supply constraint could put the brakes on investment before this spiral gets going.

There are numerous other avenues of research related to generating embodied technological change and the immediate and long-run economic consequences of embodied technological change.  It is hoped that this dissertation will aid in the pursuance of this research and will itself contribute to the understanding of these phenomena.

# Appendix A

**Variable Construction and Sample Characteristics for the Plant-Level Samples**

## 1. Variable Construction

Each of the data samples described in Section 5 of Chapter 2 contain the same variables. The definitions of gross output, labor, structures capital stock, materials, and energy are similar to those used in the plant-level literature (see Center for Economic Studies (2000)). The Real gross output was defined as value of shipments plus inventory change deflated by the 4-digit SIC shipments deflator in the NBER-CES data base (see Bartelsman and Gray (1996)). The concept of "production-worker equivalent hours" was used for the labor variable:

$$L = ph + (nw/pw)\,ph\,,$$

where ph is production worker hours, nw is total nonproduction worker salaries and wages, and pw is total production worker salaries and wages. Assuming workers are paid their marginal product, the second term should capture "production worker equivalent hours" contributed by nonproduction workers. Real energy expenditures is measured as the sum of the costs of fuel and electricity deflated by the NBER-CES energy deflator. Real materials is the sum of the costs of fuel, electricity, and parts, deflated by the NBER-CES materials deflator.

The structures capital stock is defined according to the tradition perpetual inventory definition:

$$S_t = \sum_{j=1}^{T} I_{t-j}^{S} D_{t,t-j} \qquad ,$$

where T is the age of the plant, $I^S$ is new structures investment (deflated using 3-digit structures investment deflators from the FRB), and $D_{t,t-j}$ is the fraction of structures investment of vintage t-j that remains productive in year t. We describe below the construction of these age-efficiency profiles for structures and equipment, $D_{t,t-j}$, for each 3-digit SIC industry.

## 2. Physical Depreciation Measures

We employ the methodology used by BLS and FRB in constructing capital stocks adjusted for the effects of physical depreciation (for details see Mohr & Gilbert (1996)). For each vintage of investment we repeat the following procedure. First, the industry-level capital expenditures are split among 35 asset categories. This is accomplished with an iterative matrix balancing (RAS) technique that employs the industry-level investment data as column controls and utilizes (aggregate-economy) NIPA data on asset-level capital expenditures as row controls for the 35 asset categories. Data derived from BEA's Capital Flows Tables (CFT) provide initial asset-by-industry investment shares for the iterative procedure.

Second, these asset expenditures by industry are transformed from a current-dollar to a constant-dollar basis to obtain estimates of real investment by asset type that can be compared across time. All assets are deflated using the PCE deflator. Third, we use mean service lives that are specific to each asset type and adjusted to account for expected retirements from each asset-type investment bundle around its mean life. These mean service lives were supplied by BEA except for autos. A discard density function captures stochastic retirements around these mean lives, whereas a hyperbolic- (or beta-) decay function captures the effect of physical deterioration due to wear and tear. We adjust real industry investment by asset type for the joint effects of the decay and discard processes rather than just the latter. In effect, we create a series for each asset of the amount of the vintage that will still be productive at age *a*. Finally, we aggregate all assets of the same vintage to derive age-efficiency schedules specific to vintage and investing-industry.

The BLS-FRB methodology has two important results. First, the age-efficiency schedule is vastly different from geometric, especially in the early part of an asset's life. Second, the implied rate of *physical* depreciation is much lower than the *economic* depreciation rates produced by the BEA.

## 3. Sample Characteristics

The special characteristics of the LRD, from which the overall data set was drawn, combined with the need to have continuous investment histories, necessitate a thorough analysis of the properties of each of the samples we use. Figures A-1 through A-13 illustrate some of these properties.

The LRD contains data from the Census of Manufacturers (CM) and the Annual

Survey of Manufactures (ASM). The CM is conducted every five years in years ending in "2" and "7". It collects data on approximately 300,000-380,000 plants. The ASM is based on a panel of plants which are sampled from the CM universe and followed for 5 years. Within the 5-year interval of an ASM panel, the Census Bureau also adds to the panel a sample of plant births for each year. A new ASM panel is selected at the beginning of the second year after a CM. Thus, the 6 ASM panels in the current LRD are 1972-73, 1974-78, 1979-83, 1984-88, 1989-93, and 1994-96. Plants are selected for the ASM based on their size and their share of industry output. Plants with more than 250 employees are sampled with certainty while smaller plants are sampled with probabilities proportional to their size.

Figure A-1 shows, for each year from 1975-96 and on average, the fraction of all U.S. manufacturing plants that are accounted for by each sample. The timing of ASM panel selection has a clear effect on the annual sample size of POST72A, POST72B, and SCREEN. There are substantial drops in sample size in the first year of each ASM panel (1979, 1984, 1989, and 1994). This can be attributed to the reselection of the ASM panel in these years which eliminates many plants from the LRD, though these plants do not necessarily cease operations. Averaged over the sample period, our primary sample, POST72A, is the smallest at 1.2% of manufacturing.[87] Including observations from plants that are observed for only two or three consecutive years (as in POST72B), we reach an average of roughly 2%. The fact that the plants in the 1972-96 panel, nearly all of which were born prior to 1972,

[1] Over the 1975-96 period, there was an average of roughly 365,000 manufacturing plants with an average of 4402 of them in the POST72A sample.

generally account for more of total manufacturing than those of POST72B shows that we sacrifice a great number of observations in order to avoid having unobserved pre-1972 investment. The SCREEN sample is able to keep many of these observations, in addition to including plants born after 1972 that survive for at least four consecutive years. Thus, it is not surprising that the SCREEN sample is the largest on average at approximately 2.8% of manufacturing.

Despite the relatively small fraction of all manufacturing plants accounted for by these samples, they represent a much higher share of manufacturing in terms of gross output (shipments), employment, and investment. This is demonstrated for shipments in Figure A-2.[88] As plants born prior to 1972 exit or shrink and plants born after 1972 enter and expand, the post-1972 samples, POST72A and POST72B, account for increasingly larger shares of manufacturing, reaching 13.4% of the total value of shipments by 1996. The expansion of post-1972 plants is also evident in the mean shipments, employment, and investment for plants in each sample (and for total manufacturing). Mean shipments by year is shown in Figures A-3. Again, the employment and investment graphs (not shown) tell a similar story. One can see a general rise over the 1975-96 period for each sample as well as for overall manufacturing. With the exception of the 1972-96 panel, the samples display a marked jump in mean activity in the beginning year of each ASM panel (1979, 84, 89, and 94). This is due to the fact that, for the most part, only large plants (having over 250 employees) are selected to consecutive ASM panels. Thus, smaller plants which were

[2] The graphs for employment and investment look quite similar.

probabilistically selected for one ASM panel are unlikely to be selected for the next panel. As all plants, and particularly those that stay in the ASM from one panel to the next, grow over time, the mean activity of plants in POST72A, POST72B, and SCREEN jumps at the start of each ASM panel.

The above effects also influence the average age, which is shown in Figure A-4. For plants born after 1972, age is simply the number of years since birth. For plants born during or prior to 1972, I make use of data from the 1975 and 1981 CM's which asked establishments to report the year they began operations. This birth year data was compiled by Davis, Haltiwanger, and Schuh (1996). As expected, the 1972-96 panel is the oldest sample followed by Screen, POST72A, and POST72B. Quite mechanically, the 1972-96 panel ages by exactly one year each year of the sample. The other samples, particularly POST72A and POST72B, have a flatter age profile over time, even having somewhat of a decline over the 1990's. Unfortunately, there is no way of knowing the true average age of manufacturing plants in the U.S.. However, it is likely to be lower than that of these samples (with the possible exception of POST72B) which by design tend to have plants that have survived for a substantial period of time.

Figures A-5 through A-8 show the mean (over 1975-96) distribution of shipments across 2-digit industries of each sample versus that of overall manufacturing (as reported in the NBER-CES Productivity Database). Each sample appears to be fairly representative. The over- or under-representation of some industries seems to be largely a function of age. For example, in our primary sample, POST72A, Petroleum (29) is substantially under-represented, while Food products (20) is over-represented.

This is because Petroleum is dominated (in terms of gross output) by large, old plants whereas food products has smaller, newer plants (as well as more plants in general).

Perhaps the best way to evaluate the representativeness of a sample is in terms of the dynamic behavior of its members. This is done in Figures A-9 and A-10, which display the growth rates of employment and gross investment for the samples and total manufacturing (published ASM). The growth rates for the samples refer to pairwise-continuous share-weighted average growth rates, in other words, the share-weighted average growth rate for year t is calculated using all (and only) plants that existed in both t and t-1. The growth rate measure used here is the symmetric and bounded "g" measure used in Davis, Haltiwanger, and Schuh (1996):

$$g_{it} = \frac{X_{it} - X_{it-1}}{(X_{it} + X_{it-1})/2}$$

for any variable X. The (Divisia) share-weighted average of $g$ across all pairwise-continuous plants, $\bar{g}$, is calculated using the share of plant I's X in total manufacturing's X:

$$\bar{g}_t = \sum_{i=1}^{N_t} \frac{X_{it}}{X_t} \cdot g_{it} \quad \text{where} \quad X_t = \sum_{i=1}^{N_t} X_{it} .$$

The SCREEN and the 1972-96 panel samples appear to underestimate the growth in employment in the 1990's. There also appears to be an underestimation of the growth in new investment in the POST72A sample in 1976 and in the POST72B sample from 1976-81. Nevertheless, it is clear that all four samples generally track aggregate manufacturing fairly closely.

# Appendix B

## Industry-Level Real Output Data

This appendix describes the sources of industry-level real output data used in Chapters 3, 4, and 5. The table below lists the 54 industries and the source of real output data for each.

### Table B-1 Sources of Real Output Data

| | |
|---|---|
| 1 Agriculture, forestry and fisheries | Value & quantity data from USDA. |
| 2 Metal mining | Value and quantity data from Minerals Yearbook, Energy Statistics Sourcebook. |
| 3 Coal mining | |
| 4 Crude petroleum and natural gas | |
| 5 Non-metallic mining | |
| 6 Construction | Nominal and real output estimated from unpublished NIPA PCE data. |
| 7 Food and tobacco products | Data for all manufacturing industries is from the Annual Survey of Manufacturers and Economic Census (U.S. Census Bureau). Nominal Output data is based on reported product shipments. Price deflators come from BEA's shipments deflators (Producer Price Index Revised, PPIR), except computers. |
| 8 Textile mill products | |
| 9 Apparel and other textile products | |
| 10 Paper and allied products | |
| 11 Printing and publishing | |
| 12 Chemicals and selected chemical products | |
| 13 Plastics and synthetic materials | |
| 14 Petroleum refining and related products | |
| 15 Rubber and miscellaneous plastics products | |
| 16 Footwear and leather products | |
| 17 Lumber and wood products | |
| 18 Furniture | |
| 19 Stone, clay and glass products | |
| 20 Primary iron and steel | |
| 21 Primary nonferrous metals manufacturing | |
| 22 Metal products | |
| 23 Engines and turbines | |
| 24 Agricultural, construction & mining machinery | |

| | |
|---|---|
| 25 Metalworking machinery | |
| 26 Special industry machinery | |
| 27 General and miscellaneous industrial machinery | |
| 28 Computers and office equipment | |
| 29 Service industry machinery | |
| 30 Electrical industrial equipment and apparatus | |
| 31 Household appliances, elec lighting & wiring | |
| 32 Audio, video and communication equipment | |
| 33 Electronic components | |
| 34 Motor vehicles and equipment | |
| 35 Aircraft and parts | |
| 36 Ships and other transportation equipment | |
| 37 Instruments | |
| 38 Miscellaneous manufacturing | |
| 39 Railroad transportation | Same source as for industries 41-52 below. |
| 40 Air transportation | Nominal and real output based on data from U.S. Statistical Abstract. |
| 41 Trucking and other transport | Nominal and real output come from BLS's Office of Employment Projections. According to the Nov. 1999 Monthly Labor Review, data sources for nonmanufacturing industries "include the Service Annual Survey, National Income and Product Accounts (NIPA) data on new construction and personal consumption expenditures, IRS data on business receipts, and many other sources. The constant dollar industry output estimates for the most recent years are based on BLS employment data and trend projections of productivity." It is unclear how the BLS obtains real output prior to "recent" years. |
| 42 Communications services | |
| 43 Electric utilities | |
| 44 Gas, water and sanitary services | |
| 45 Wholesale trade | |
| 46 Retail trade, restaurants & bars | |
| 47 Finance and insurance | |
| 48 Real estate and rental | |
| 49 Hotels, repairs except auto | |
| 50 Business and professional services | |
| 51 Automotive repair and services | |
| 52 Movies and amusements | |
| 53 Health services | Nominal and real output data based on PCE from unpublished NIPA. |
| 54 Educational and social services and nonprofit organizations | |

# Appendix C

## New C++ Routines for Calculating Capital Stocks, Productivity, and Hours

The core program of IDLIFT is **model.cpp**. This program contains the main model loop within which is the real-side loop and the price-side loop. Within the real side loop is the investment-output loop and within this loop productivity and employment are calculated. The schematic below shows the organization of **model.cpp**:

*For t = godate until t= stopdate:*

*Model loop: load vectors and matrices, read fixes, initialize output and prices*

*Real-side loop:*

*Call to PCE function*

*Call to exports function*

*Investment-Output loop:*

*Call to equipment investment function*

*Call to construction function*

*Call to government spending function*

*Solve for output given results of above functions*

***Calls to productivity, hours, and employment functions***

*(see detail below)*

*Price/income-side loop:*

*Calls to functions calculating value added components*

*Solve for prices given results of value added functions*

*Calculate aggregate variables*

*End of model loop: t = t + 1*

Within the calls to the productivity, hours, and employment functions, I placed the new routines (called UpdateKBuckets(), DanProductivity(), and ReviseEmploy() below) *after* calls to the preexisting functions for productivity, average annual hours, and employment. This section of **model.cpp** is excerpted below (the new functions are in bold):

```
// (*****) Productivity and Employment :
if(t>=prd.LastData() ) {
       update(out,Outlag);
       Productivity(hrs, prd, Outlag, qpeak, Qpeaklag, eqi, caphat,
              Caphatlag, pdm, iag56, ProductivityEquations, prdtrnd);
       }
// (*****) Average Hours Worked function:
if(t>=yhr.LastData() ) {
       AvgHours(yhr,Outlag,AverageHoursEquations);
       othrsf();  // dom serv., govt. ent.
       }
// Call Employ to calculate employment, and various identities:
p5 = pdm[5];
if(t>=emp.LastData() ) {
       Employ(emp,hrs,prd,yhr,out);
       }
if(t>dprd.LastData() ) {
       str.fix(t);
       UpdateKBuckets(vi, vbk1_, vbk2_, vbk3_, qastk, vbk1lag,
              vbk2lag, vbk3lag, eqicu, DanProductivityEquations,
              str, strcap, Strcap, Qastk);
       }
```

```
if(t>=dprd.LastData() ) {
       DanProductivity(dhrs, dprd, qag, qagpeak, Qagpeaklag, qastk,
       Qastk, strcap, Strcap, iag56, DanProductivityEquations, hrsag);
       }
// By setting dhrs.LastData > last forecast year, we can get model
//  to compute dprd and dhrs BUT WITHOUT feeding them back into the
//  model.
if(t>=emp.LastData() && t>=dprd.LastData() && t>=dhrs.LastData() ) {
       ReviseEmploy(emp, dhrs, hrs, yhr, prd, out, iag56);
       }
```

The vectors calculated by the functions called in this section are: productivity by 97 sectors (**prd**), average annual hours by 97 sectors (**yhr**), employment by 97 sectors (**emp**), productivity by 55 industries (**dprd**), structures capital by 55 industries (**strcap**), quality-adjusted equipment capital by 55 industries (**qastk**), and hours by 55 industries (**dhrs**). A vector name followed by ".LastData()" returns the year which is the last year for which there is historical data (this information is stored in a separate file). When or if the new routines feed back into the model can be controlled by setting the last data year. Setting the last data year to the first year of the model run will fully incorporate the new routines into the model. Setting the last data year to a year greater than the last year of the forecast will allow the model to calculate **dprd** but will not allow this vector to affect the rest of the model; rather, the rest of the model will use the old productivity, hours, and employment vectors.

Thus, the old productivity and employment functions are called whether or not the new vectors are feeding back into the model. Besides making the turning on and off of the new routines extremely simple, having the old functions always called provides a convenient and time-varying vector, namely **hrs**, to be used as a "split vector" for disaggregating **dhrs** (55×1) to the 97-sector level.

The first new function, UpdateKBuckets, takes in the equipment investment and structures forecasts and calculates capital stocks. Here is the code for this function:

```
// Apply Structures fixes here so as to exogenously supply str with values
str.fix(t);

// Private Structures Buckets:
arith("In UpdateKBuckets, before STR:",t);
for(i=1;i<=NEQI;i++) {
       if(i>=55) continue;
   tempstr = str[i];
   lagstrcap = Strcap[1][i];
   tempsp = sp[i];
       tempstrcap = (1.-sp[i])*Strcap[1][i] + str[i];
       strcap[i] = (1.-sp[i])*Strcap[1][i] + str[i];
       }

// Private Equipment Buckets:
//arith("In UpdateKBuckets, before EQI:",t);
for(k=1;k<=NEQI;k++) {
       if(k>=55) continue;
   tempapc = apc[t];
   tempeqicu = eqicu[k];
   tempgamma = P[k][7];
   temp = (eqicu[k]/apc[t])*exp((t-1987)*safelog(1.+P[k][7]));
   vi[k] =  (eqicu[k]/apc[t])*exp((t-1987)*safelog(1.+P[k][7]));
   vbk1_[k] = (1.-0.14)*vbk1lag[1][k] + vi[k];
   vbk2_[k] = (1.-0.3)*vbk2lag[1][k] + 0.129*vbk1lag[1][k];
   vbk3_[k] = (1.-0.3)*vbk3lag[1][k] + 0.3*vbk2lag[1][k];
   qastk[k] = vbk1_[k] + vbk2_[k] + vbk3_[k];
       }
```

The quality-adjusted equipment capital stock (**qastk**) and structures capital stock (**strcap**) vectors are then passed (along with the 55-level output vector (**qag**) and the coefficients for the productivity equations, which are stored in a separate file) to the "DanProductivity" function which calculates productivity and hours at the 55-industry level. The main section of code for this function is below:

```
t1 = t-1900;
if (t>=1972)
   t2 = t-1971;
else t2 = 0;
if (t>=1992)
   t3 = t-1991;
else t3 = 0;

n = P.neq;
/* For each number i, for each equation, gives us the number of sectors*/
for(i = 1; i <= n; i++){
       j = P.sec(i);
       which = P.type(i);
       if(j==86)
              Oliver=small;

       // i is the equation #, j is the sector #
       if(j<=0)
              continue;
       if(which>='a' && which <= 'f') {
              arith(" in Danprod before dq calculations, sector:",j);
              Qup=Qdown=0.0;
              curqag=qag[j];
              peakqag=Qagpeak[0][j];
              peaklag=Qagpeak[1][j];
              if(curqag <= 0. || peaklag <= 0) {
                     cprintf("\r\n\r\nIn Danprod:Negative or zero output in
                            sector %d:"   " curqag=%12.1f
                            lagqagpeak=%12.1f\n\r",
                            j,qag[j],Qagpeak[1][j]);
                     trouble(NEGOUT);
                     dymetap();
                     continue;
                     }
              else dq = safelog(curqag) - safelog(peaklag);
              /* Difference of log of Output and Peak output  */
              arith(" in Danprod after dq, sector:",j);
              if(dq<0)
                     Qdown=-1.0*dq;  //thats right, in my eqns qdown is always
                         positive

              else Qup=dq;
              #ifdef DBG_PRD
              #endif
              }
       if(which=='a') {
              stuff = 1/(1-P[i][2]-P[i][3]);
              depend = stuff*( P[i][1] + P[i][2]*safelog(qastk[j])
                     + P[i][3]*safelog(strcap[j])
                     + P[i][6]*t1 - (P[i][2] + P[i][3])*safelog(curqag) );
      }
       if(which=='b') {
              stuff = 1/(1-P[i][2]-P[i][3]);
              depend = stuff*( P[i][1] + P[i][2]*safelog(qastk[j])
                     + P[i][3]*safelog(strcap[j]) + P[i][4]*Qup + P[i][5]*Qdown
                     + P[i][6]*t1 - (P[i][2] + P[i][3])*safelog(curqag) );
      }
       if(which=='c') {
              stuff = 1/(1-P[i][2]-P[i][3]);
              depend = stuff*( P[i][1] + P[i][2]*safelog(Qastk[1][j])
                     + P[i][3]*safelog(Strcap[1][j])
```

```
                    - (P[i][2] + P[i][3])*safelog(curqag) );
        }
        if(which=='d') {
                stuff = 1/(1-P[i][2]-P[i][3]);
                depend = stuff*( P[i][1] + P[i][2]*safelog(Qastk[1][j])
                        + P[i][3]*safelog(Strcap[1][j])
                        + P[i][6]*t1 - (P[i][2] + P[i][3])*safelog(curqag) );
        }
        if(which=='e') {
                depend = P[i][1] + P[i][3]*t2 + P[i][4]*Qup + P[i][5]*Qdown +
                        P[i][6]*t1;
        }
        if(which=='f') {
                stuff = 1/(1-P[i][2]-P[i][3]);
                depend = stuff*( P[i][1] + P[i][2]*safelog(qastk[j])
                        + P[i][3]*safelog(strcap[j]) + P[i][4]*t3
                        + P[i][6]*t1 - (P[i][2] + P[i][3])*safelog(curqag) );
        }

        if(depend>=7 || depend<=0) {
                cprintf("In Danprod, Sector %d  depend is CRAAAAAZY!: %12.1f\n",
                        j,depend);
                //continue;
                }
        Calc = exp(depend);
        Act = dprd[j];
        RCalc = P.rhoadj(Calc,dprd[j],i);
        dprd[j] = RCalc;
        #ifdef DBG_PRD
        fprintf(chk,"Calc = %9.2f Actual = %9.2f RCalc = %9.2f dhrs =
                %9.2f\n\n",
        Calc,Act,RCalc,dhrs[j]);
        #endif
        }
dprd.fix(t);
// Calculate 55-industry hours (DHRS):
dhrs = ebediv(qag,dprd);
return(n);
```

Finally, the "ReviseEmploy" function simply disaggregates **dhrs** (55×1) to the 97-sector level. The 97×1 vector **hrs**, which is calculated using the old productivity equations, provides the shares to be used to split out **dhrs** to the more disaggregate level when there is a one-to-many mapping from the 55-industry level to the 97-sector level. The resulting 97×1 vector is now called **hrs** (overwriting the former **hrs** vector) and 97-sector **prd** is now recalculated as **out** (97×1) divided by **hrs**. From this point on, ReviseEmploy takes **hrs** and **prd** and calculates employment just as the old "Employ" function would have with the old vectors and the rest of the model proceeds with these new vectors for **hrs**, **prd**, and **emp**.

# Appendix D
## Private and Public Construction Categories

1 1 unit res. structures
2 2 or more unit structures
3 Mobile homes
4 Additions & alterations
5 Hotels,motels,dormitories
6 Industrial
7 Offices
8 Stores,restaurants,garages
9 Religious
10 Educational
11 Hospital & institutional
12 Miscellaneous NR bldg
13 Farm buildings
14 Mining exploration shafts&wells
15 Railroads
16 Telephone & telegraph
17 Electric light & power
18 Gas & petroleum pipes
19 Other structures
20 Highways & streets
21 Military facilities
22 Conservation
23 Sewer systems
24 Water supply facilities
25 Brokers' commission

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**Figure 2-1**
**PCE deflator vs. average FRB equipment deflator used in our sample from 1972-96**

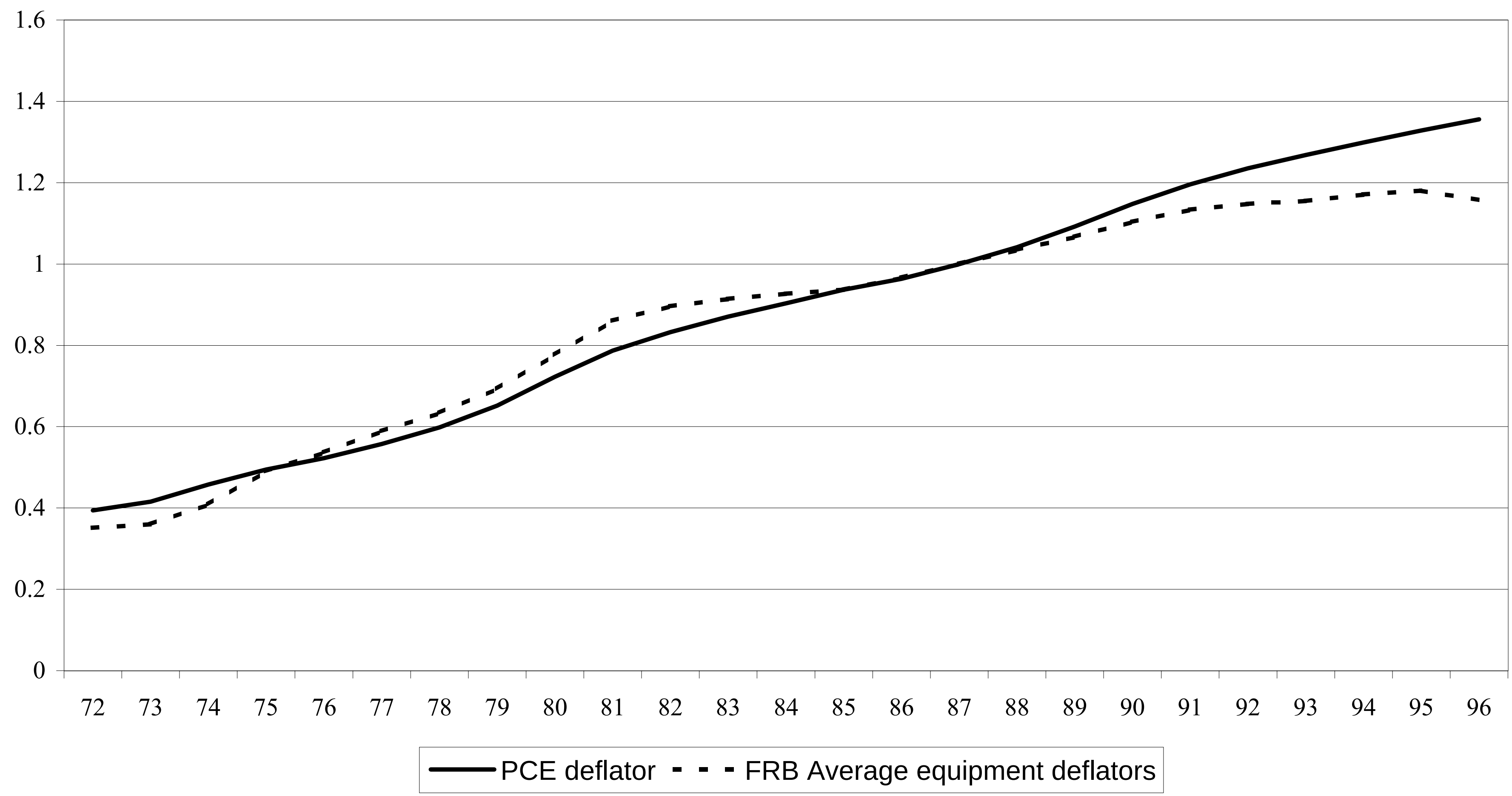


**Figure 2-2**
**Average Depreciation Pattern**

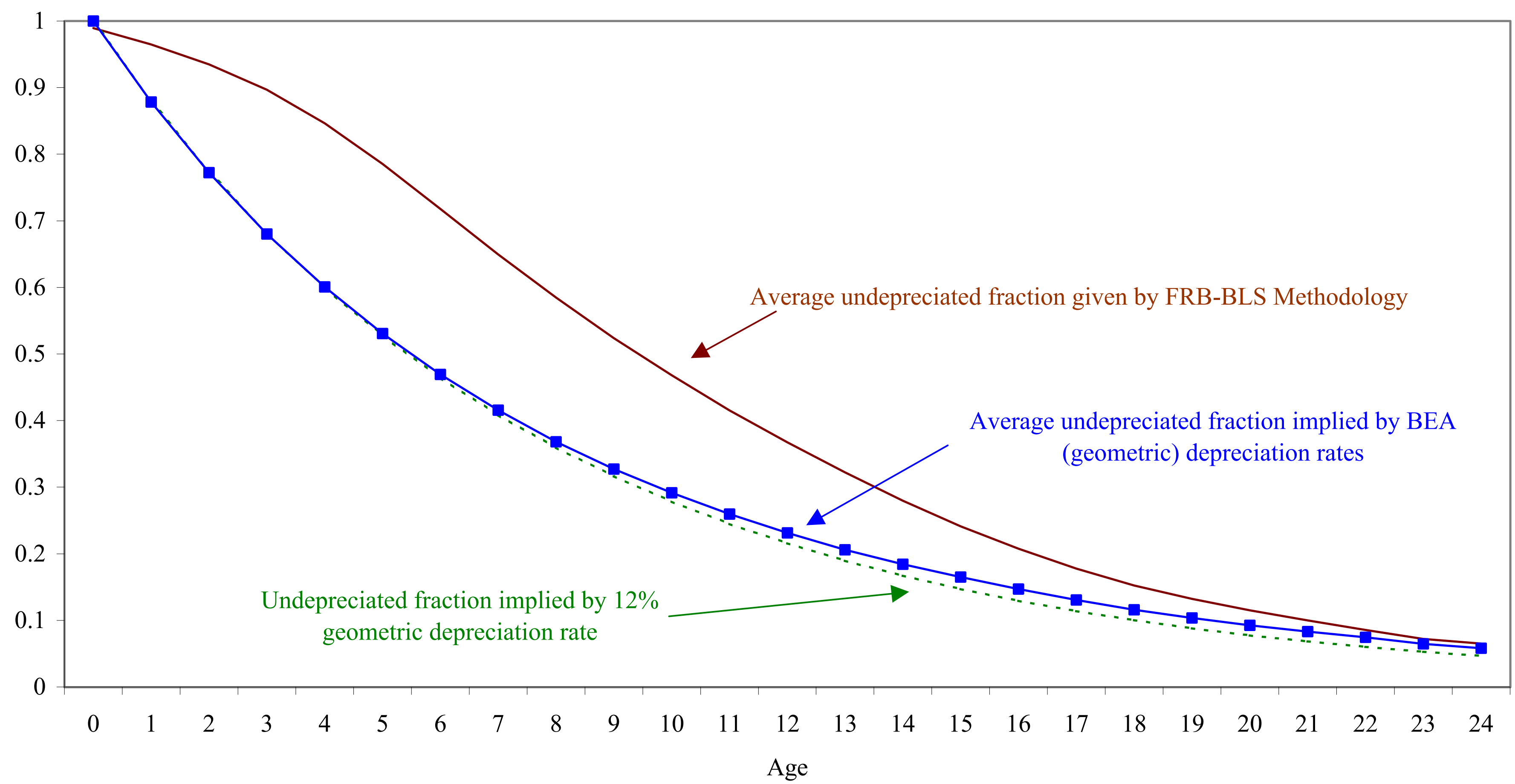
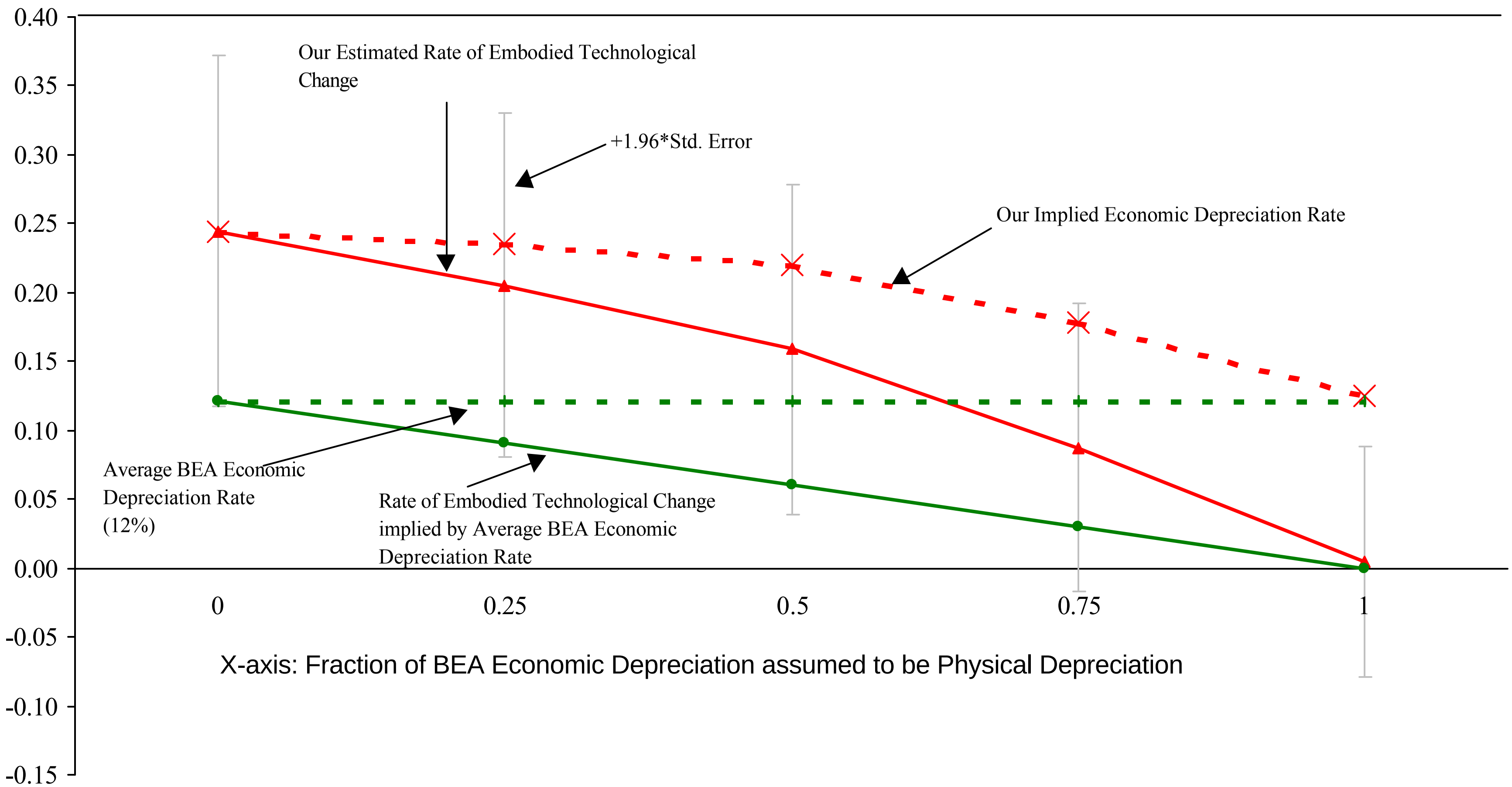


**Figure 2-3**



0.40
0.35
0.30
0.25
0.20
0.15
0.10
0.05
0.00
-0.05
-0.10
-0.15
Our Estimated Rate of Embodied Technological Change
+1.96*Std. Error
Our Implied Economic Depreciation Rate
Average BEA Economic Depreciation Rate (12%)
Rate of Embodied Technological Change implied by Average BEA Economic Depreciation Rate
0
0.25
0.5
0.75
1
X-axis: Fraction of BEA Economic Depreciation assumed to be Physical Depreciation

**Figure 3-1, Decomposition of 1972-97 q(i) growth**

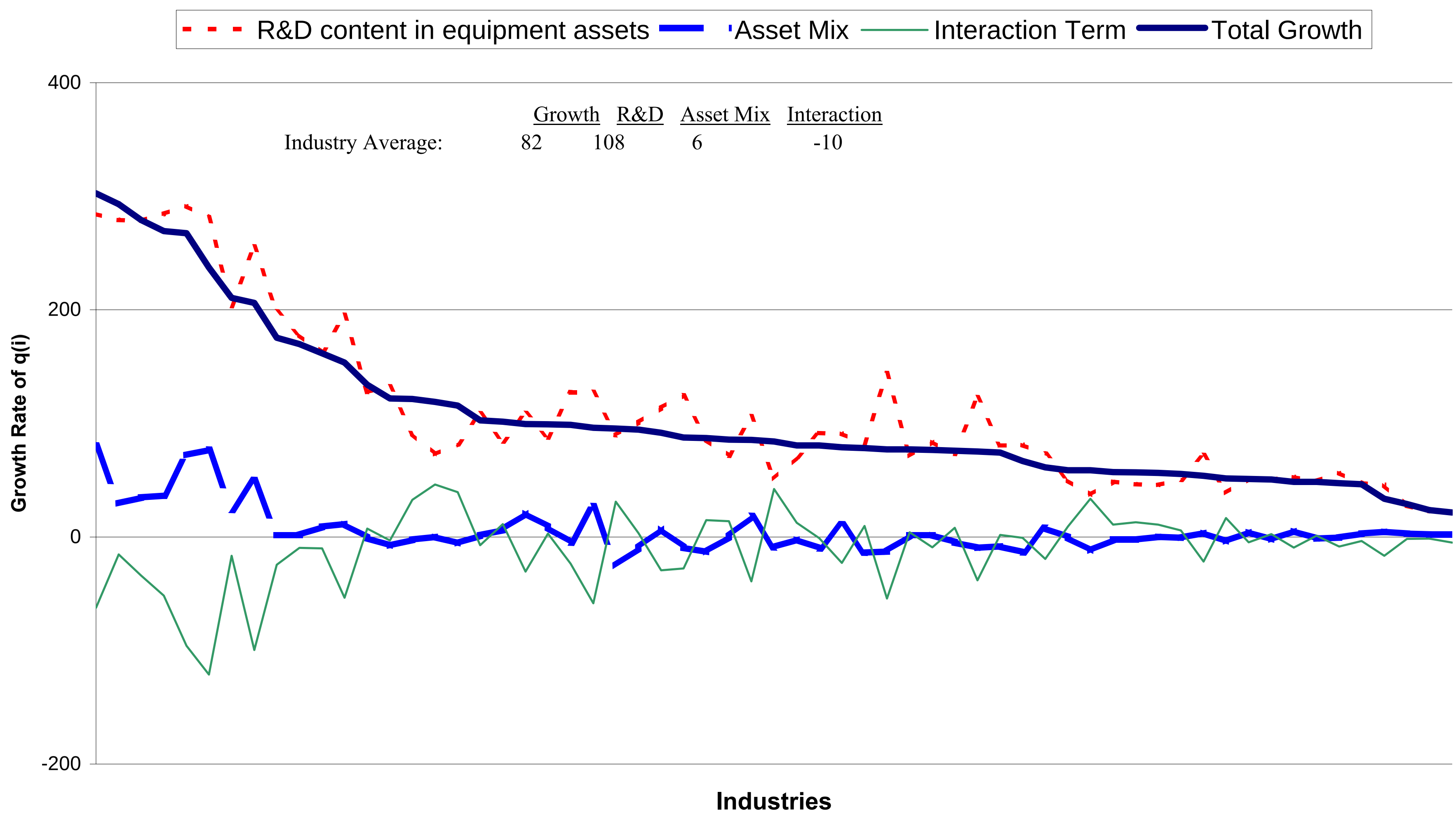


**Figure 4-1, Gridsearch Results**

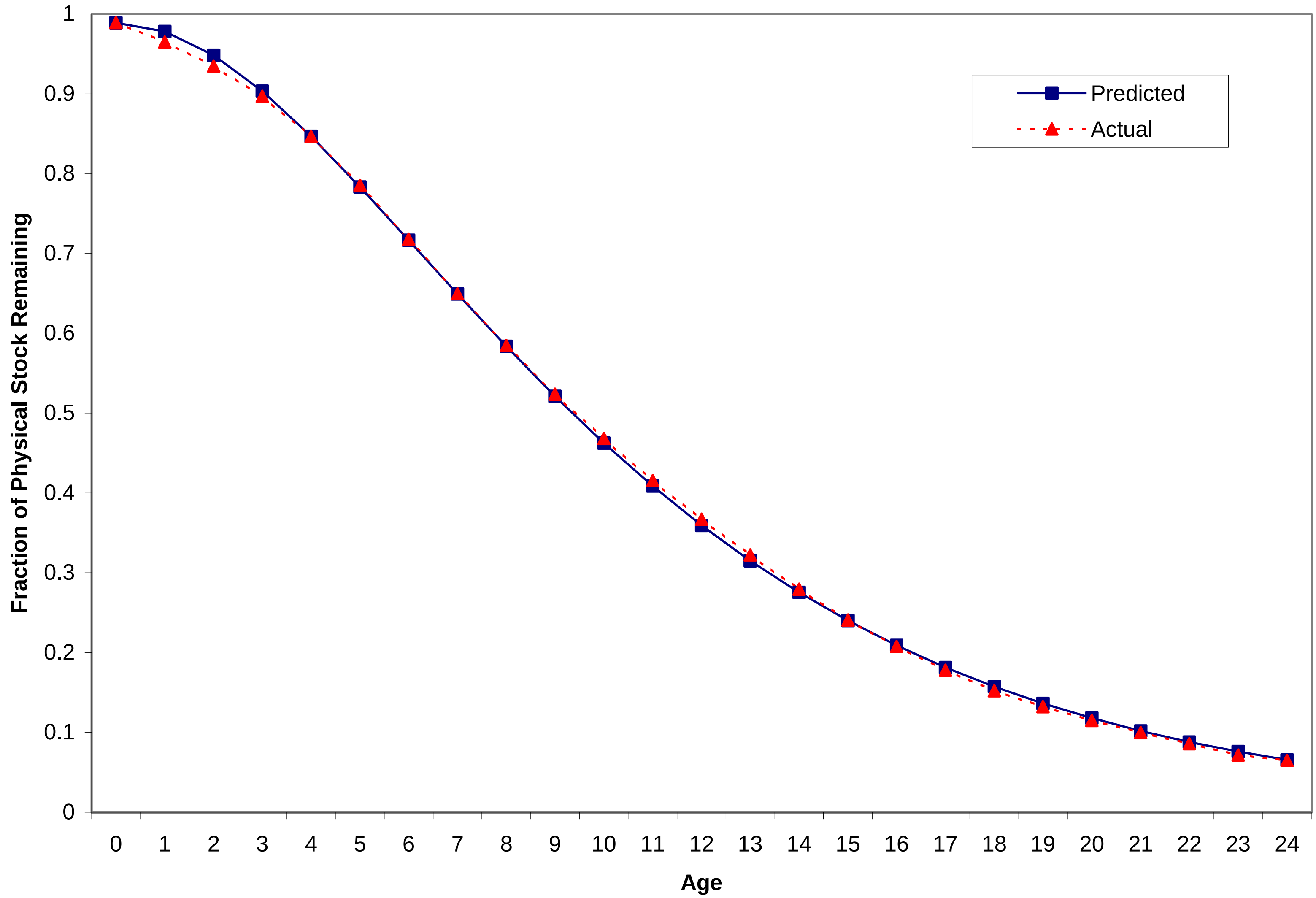


**Figure 4-2, Average Adjusted R-squared**

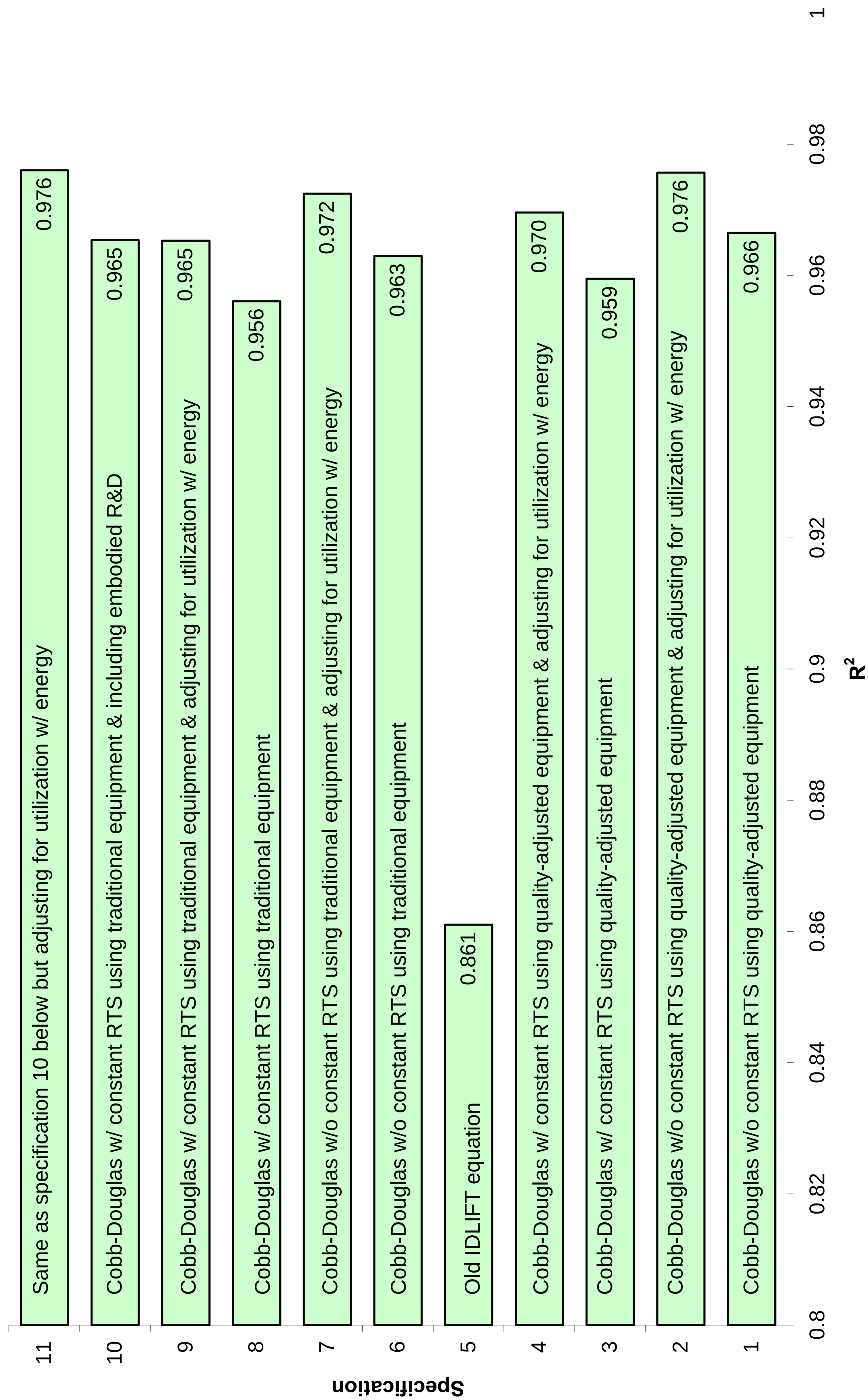


Figure 4-3, Average Elasticities

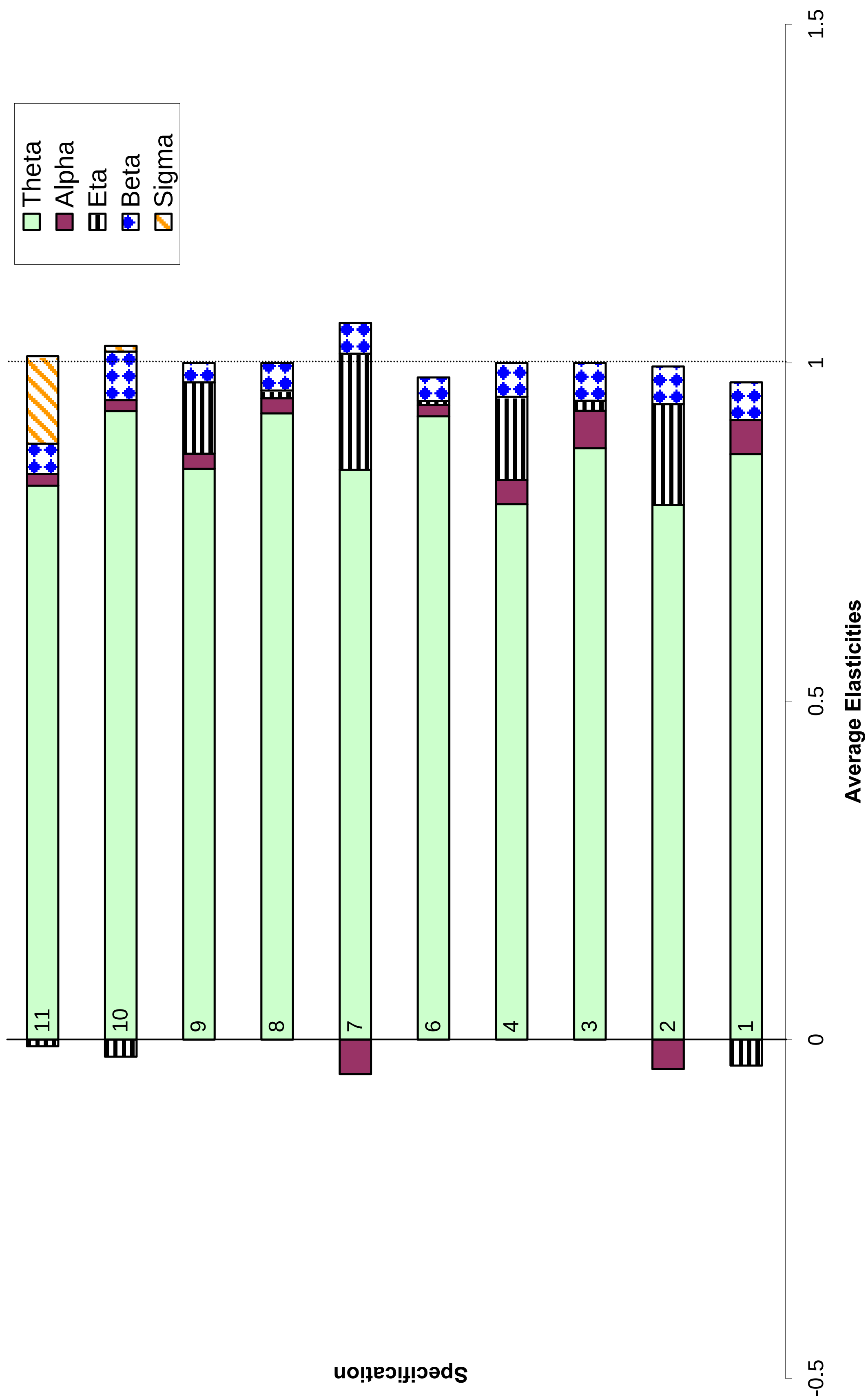


**Figure 4-4,   Percent of Elasticities that are Positive**

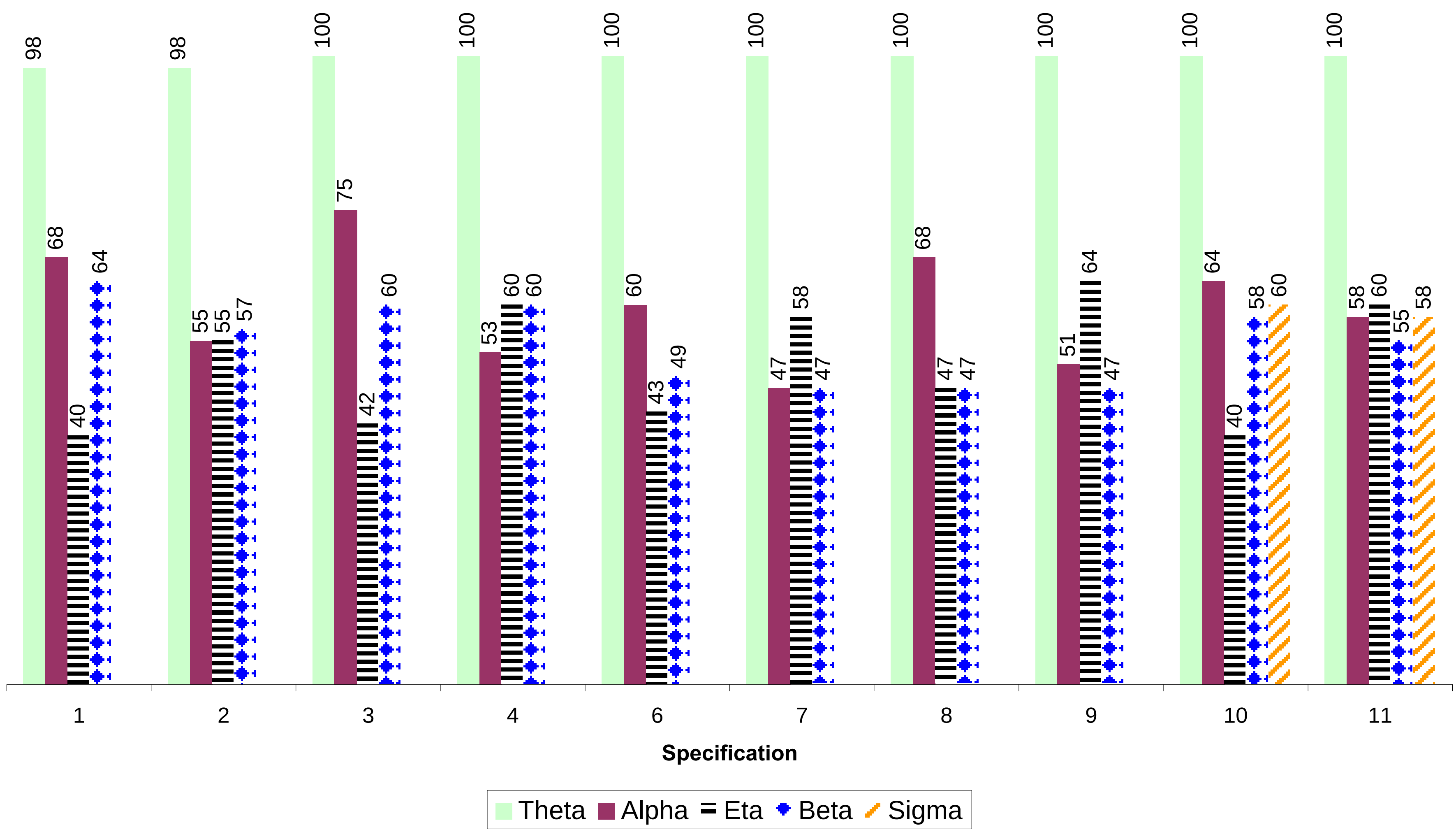


Figure 4-5, Average Tau (Elasticity of Utilization w.r.t. Energy Usage)

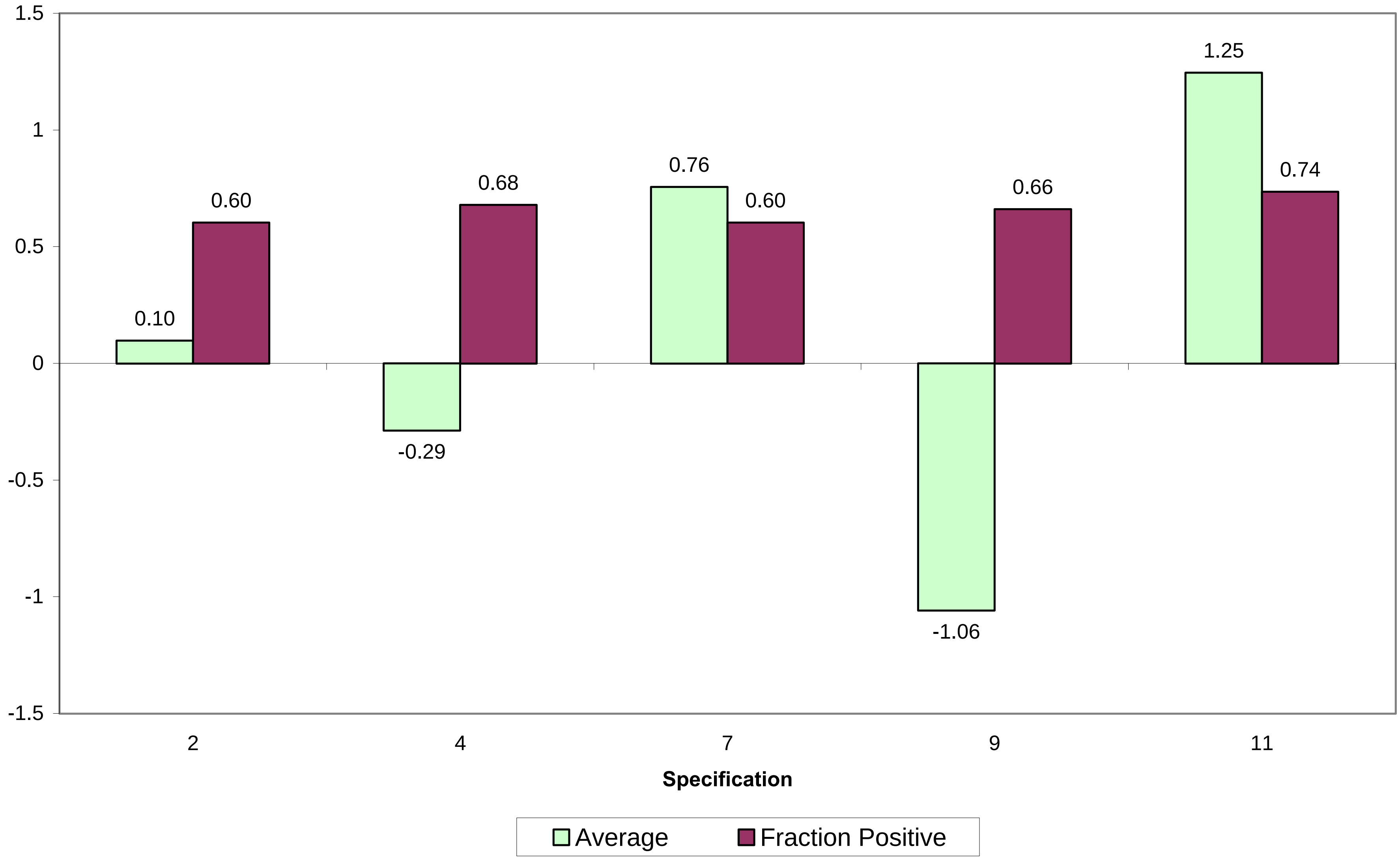


**Figure 4-6, Average Adjusted R-squared (Nonmanufacturing)**

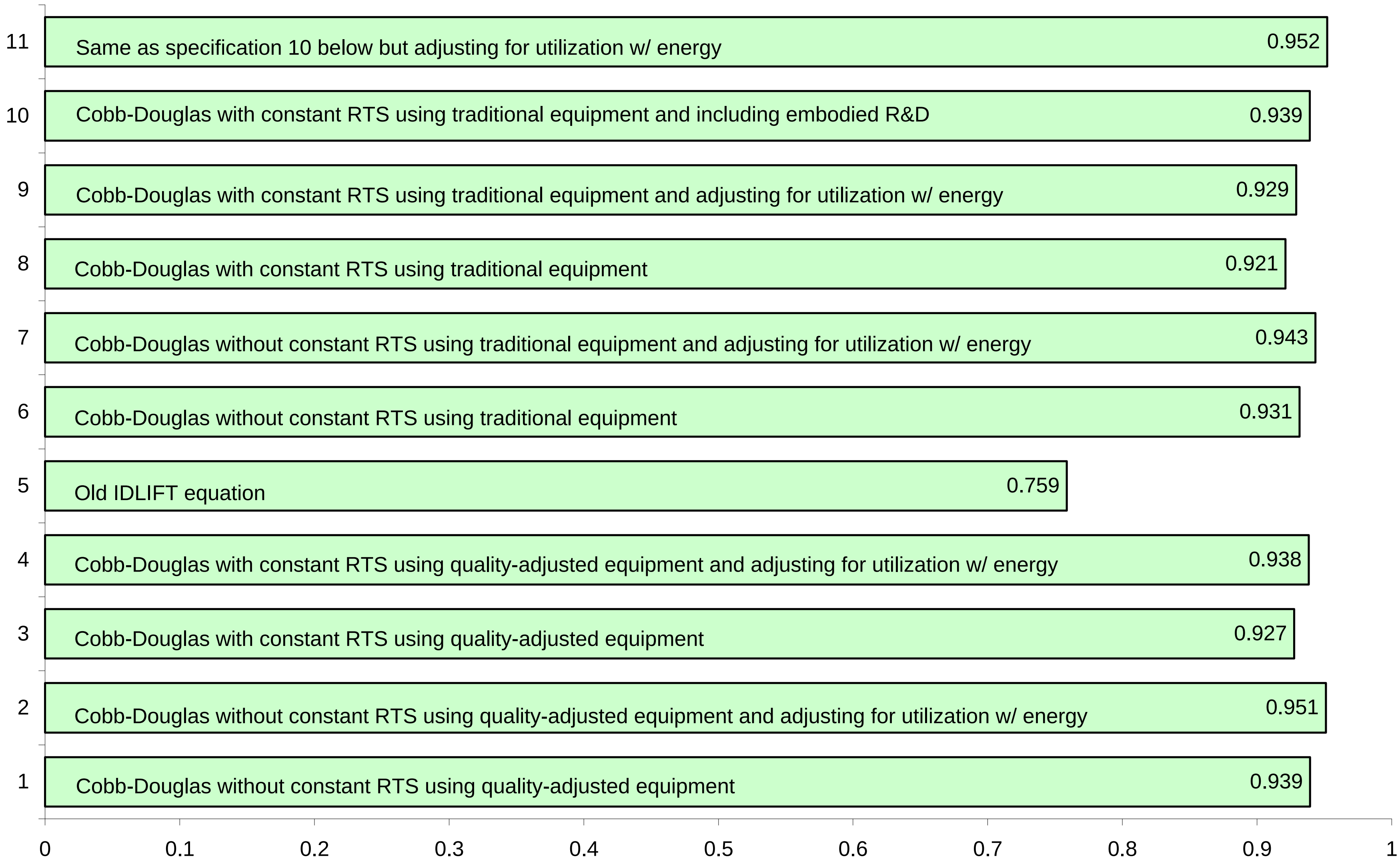
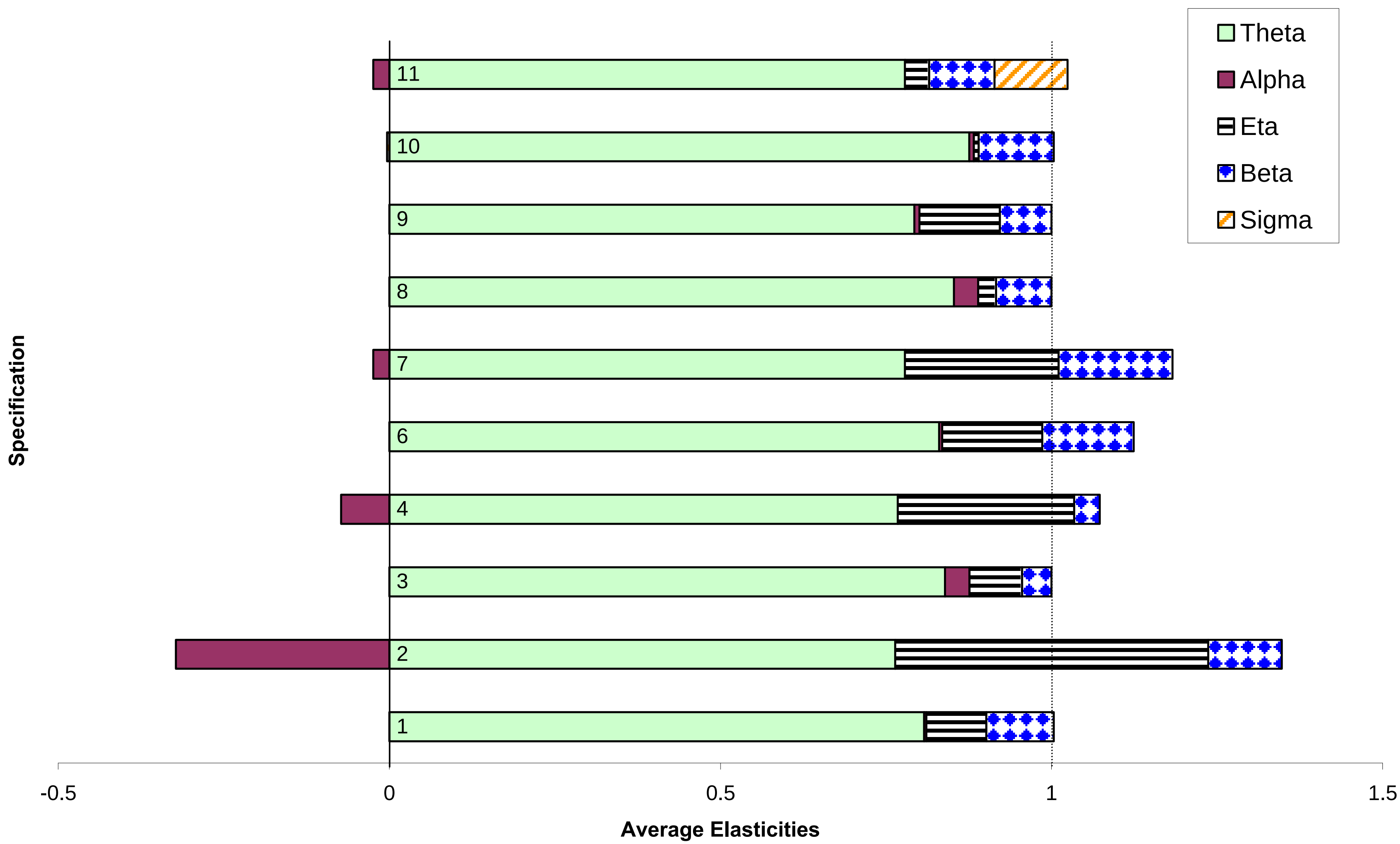


**Figure 4-7,   Average Elasticities (Nonmanufacturing)**



## Figure 4-8, Percent of Elasticities that are Positive (Nonmanufacturing)

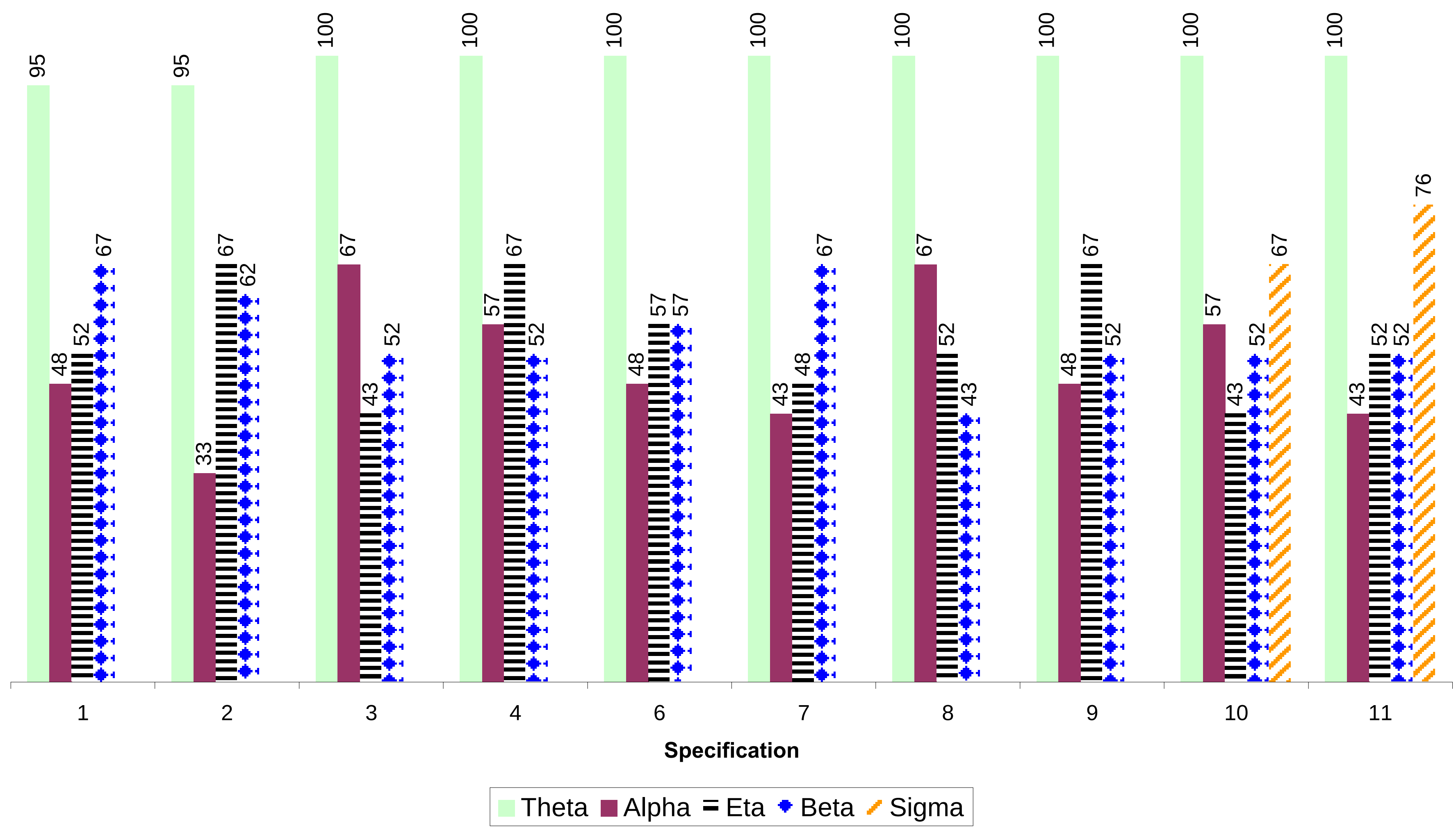


Figure 4-9,   Average Tau (Nonmanufacturing)

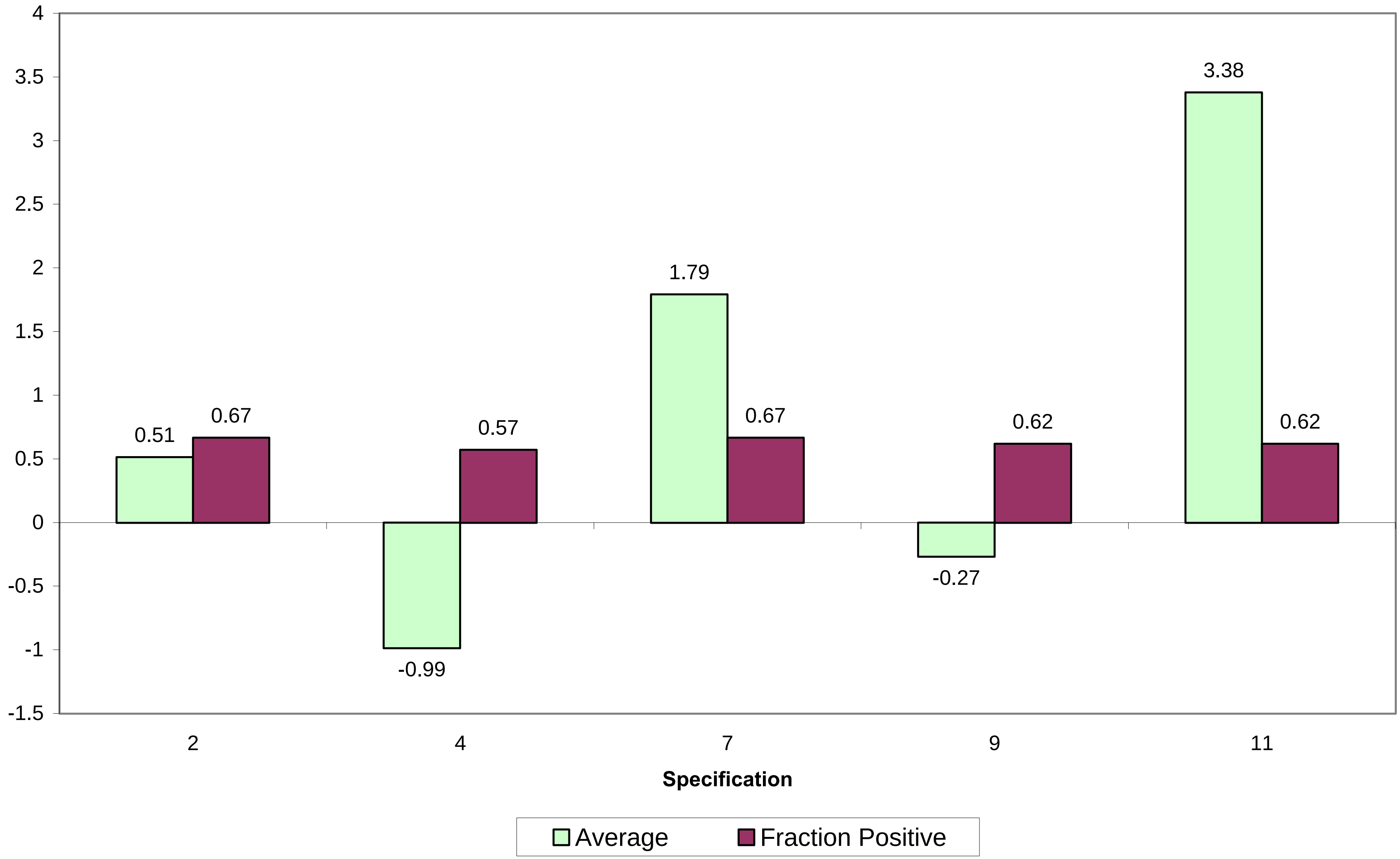


**Figure 4-10,   Average Adjusted R-squared -- Specifications Not Including Materials**

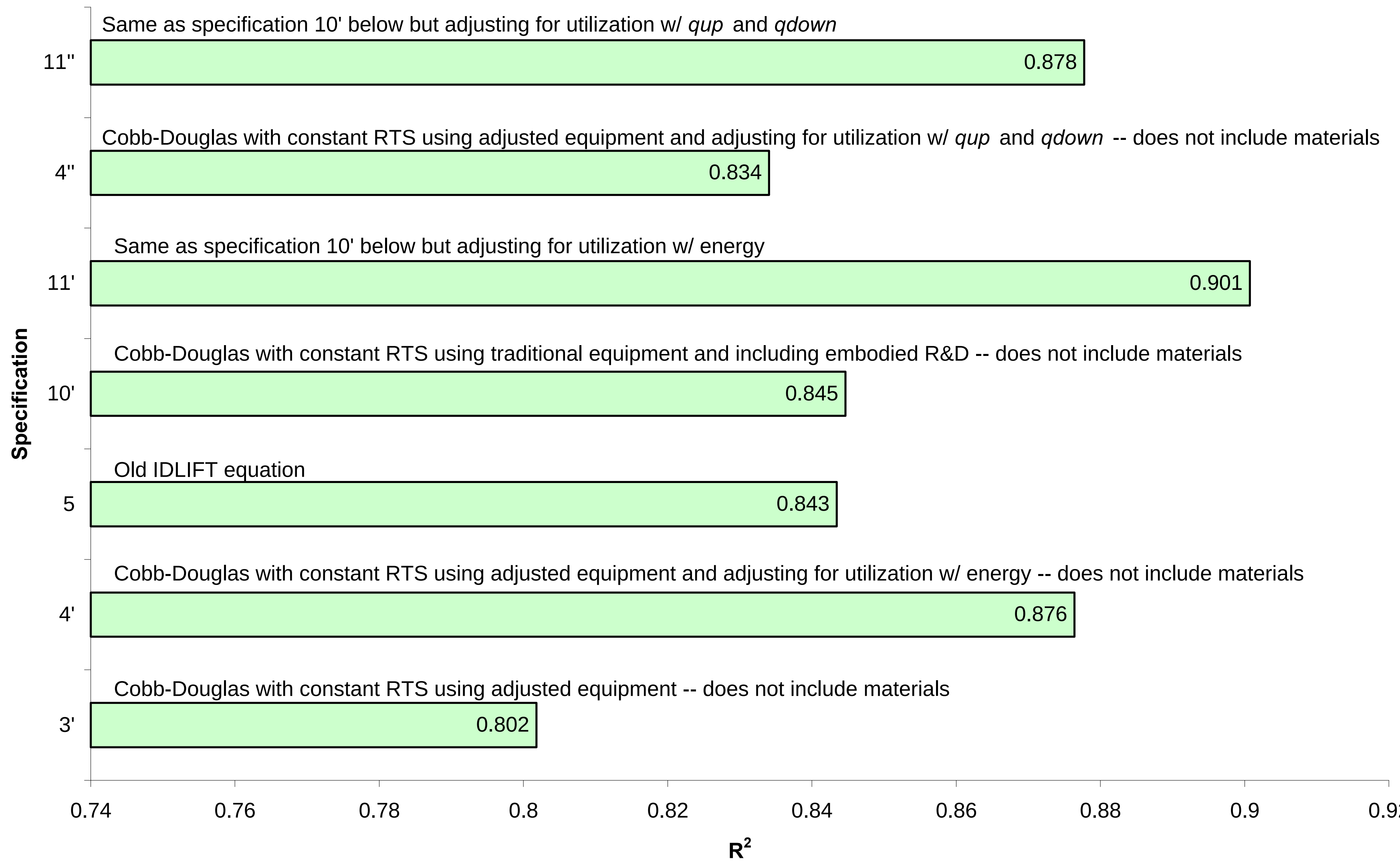


Figure 4-11,   Average Elasticities -- Specifications Not Including Materials

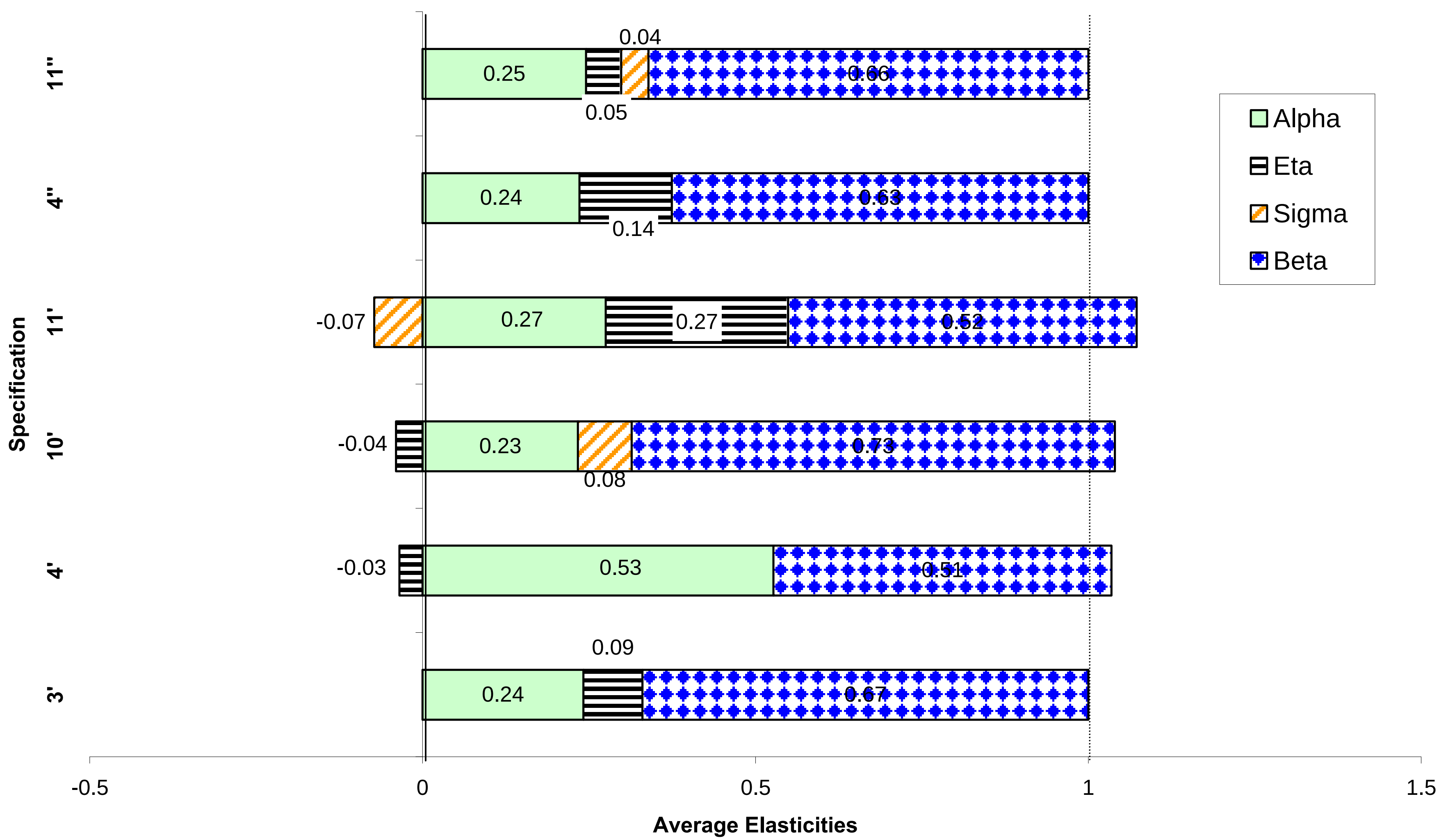


**Figure 4-12,  Percent of Elasticities that are Positive -- Specifications Not Including Materials**

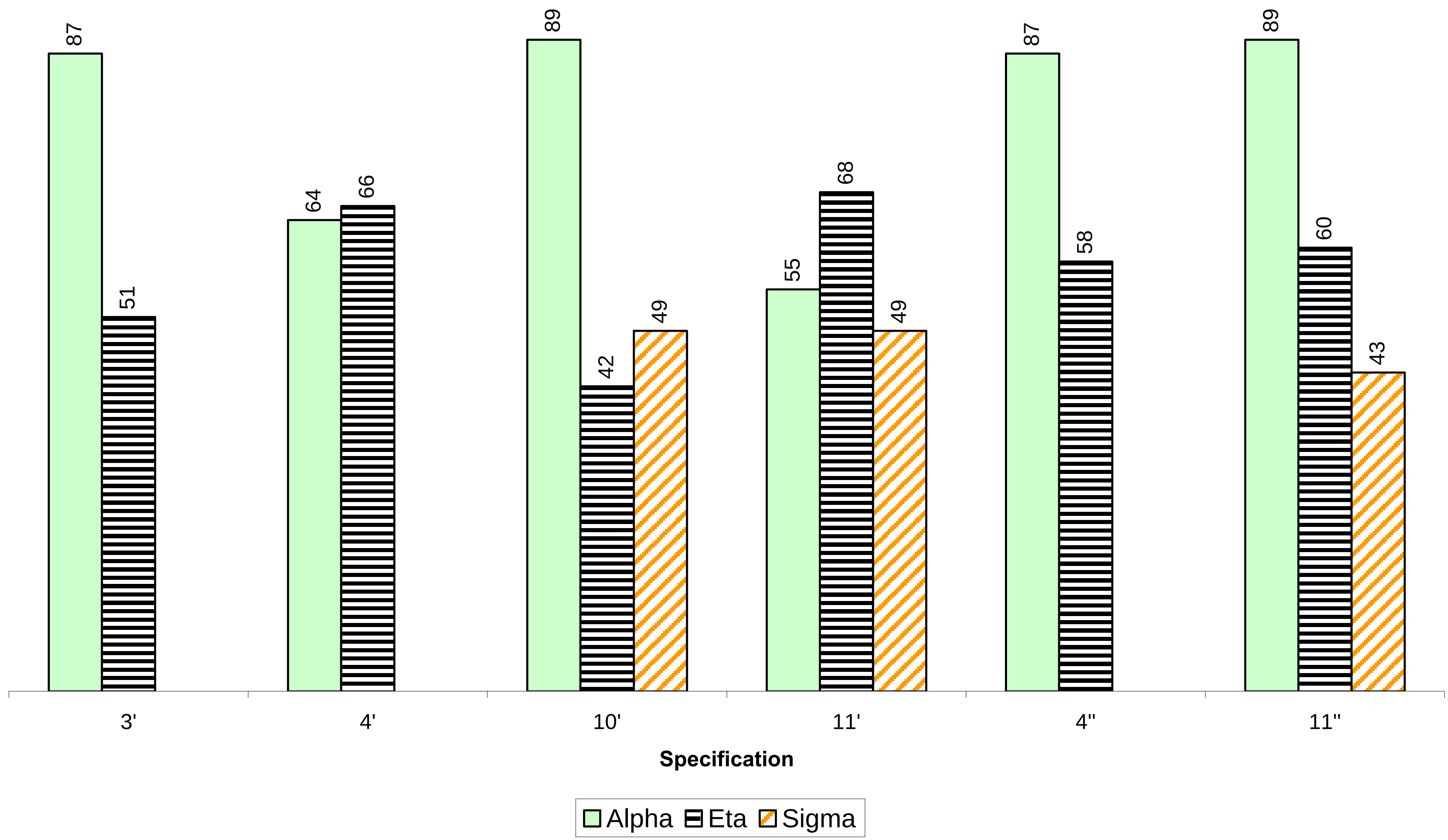


Figure 4-13, Average Tau -- Specifications Not Including Materials

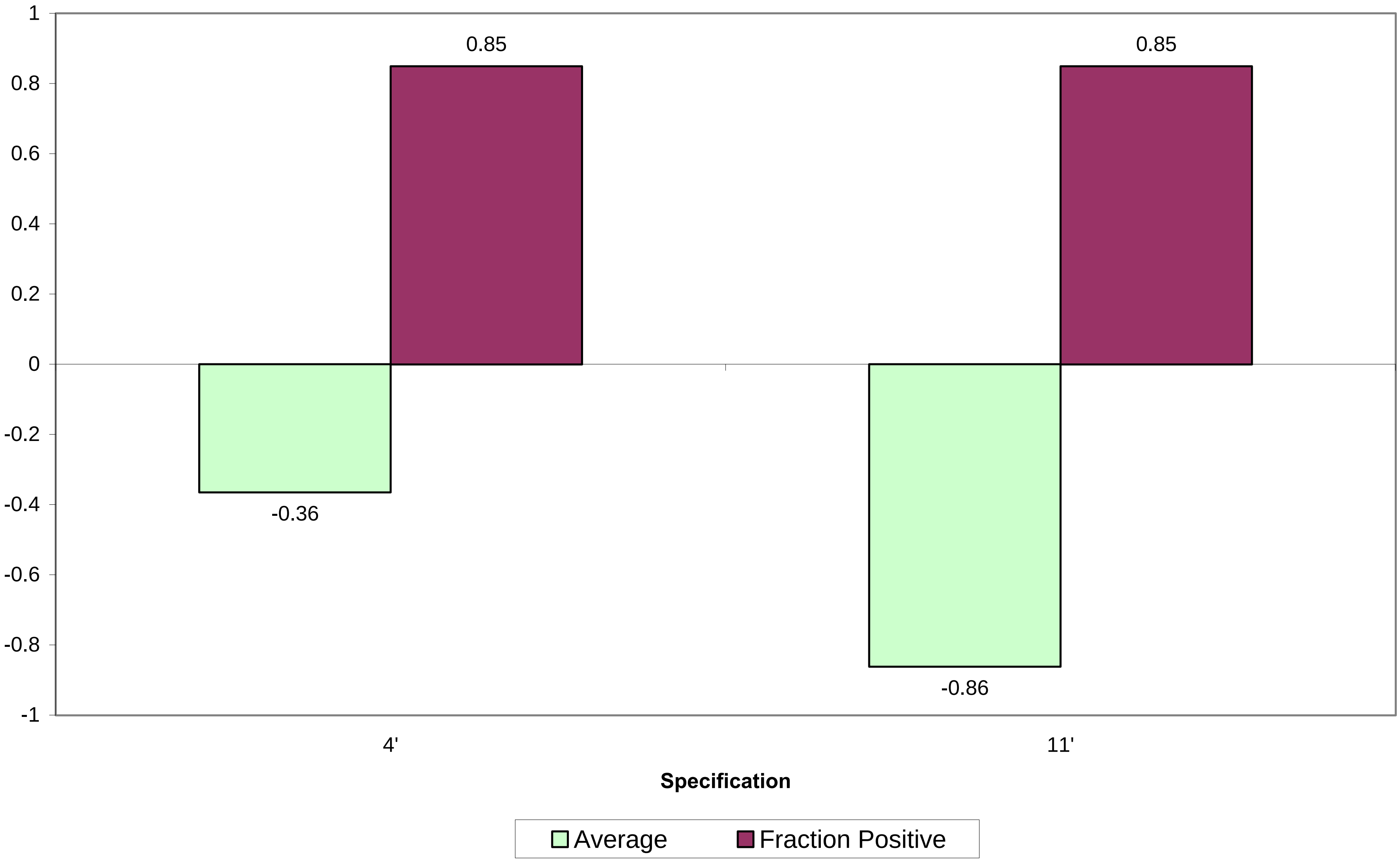


**Figure 4-14, Average Adjusted R-squared -- Specifications Not Including Materials (Nonmanufacturing)**

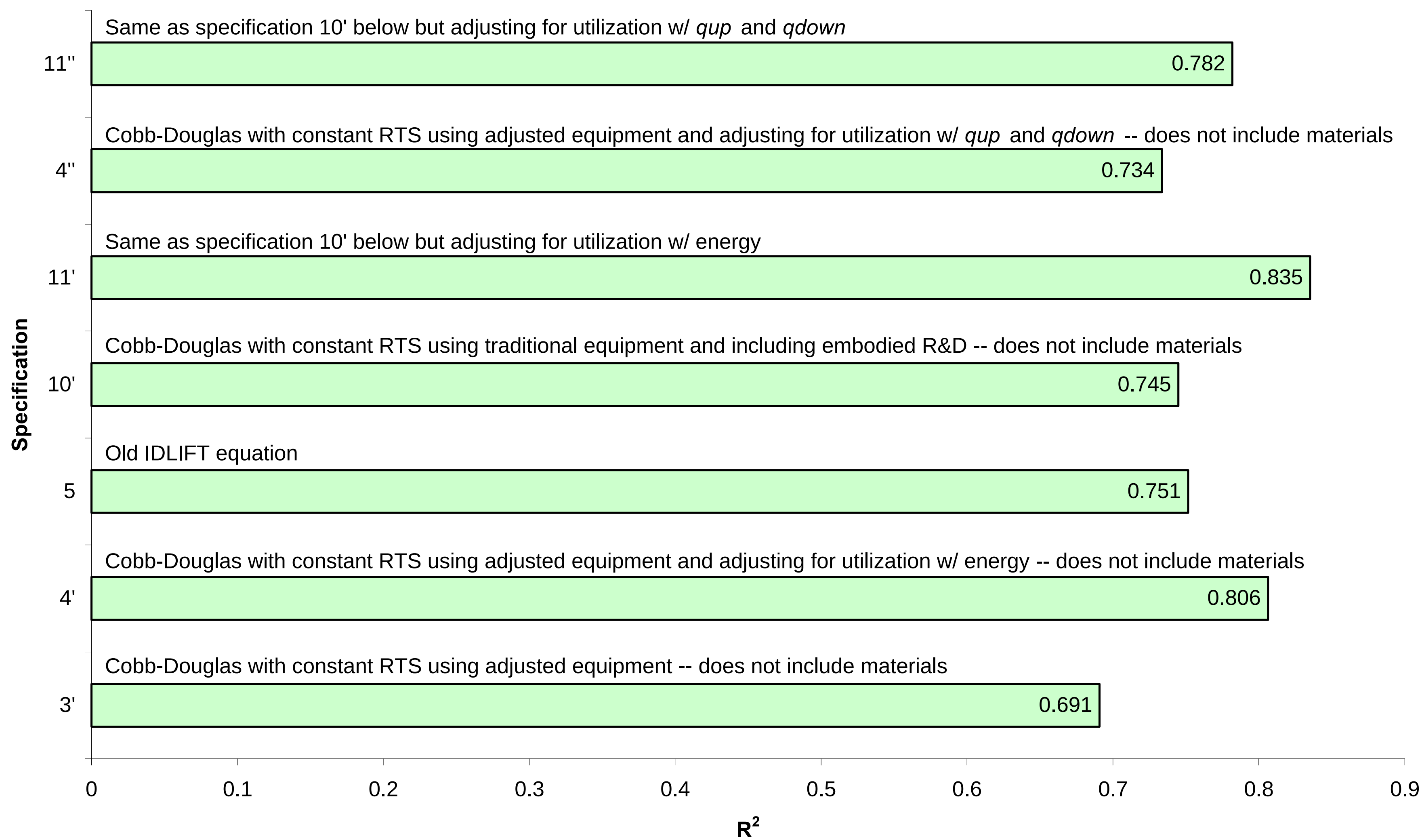


Figure 4-15, Average Elasticities -- Specifications Not Including Materials (Nonmanufacturing)

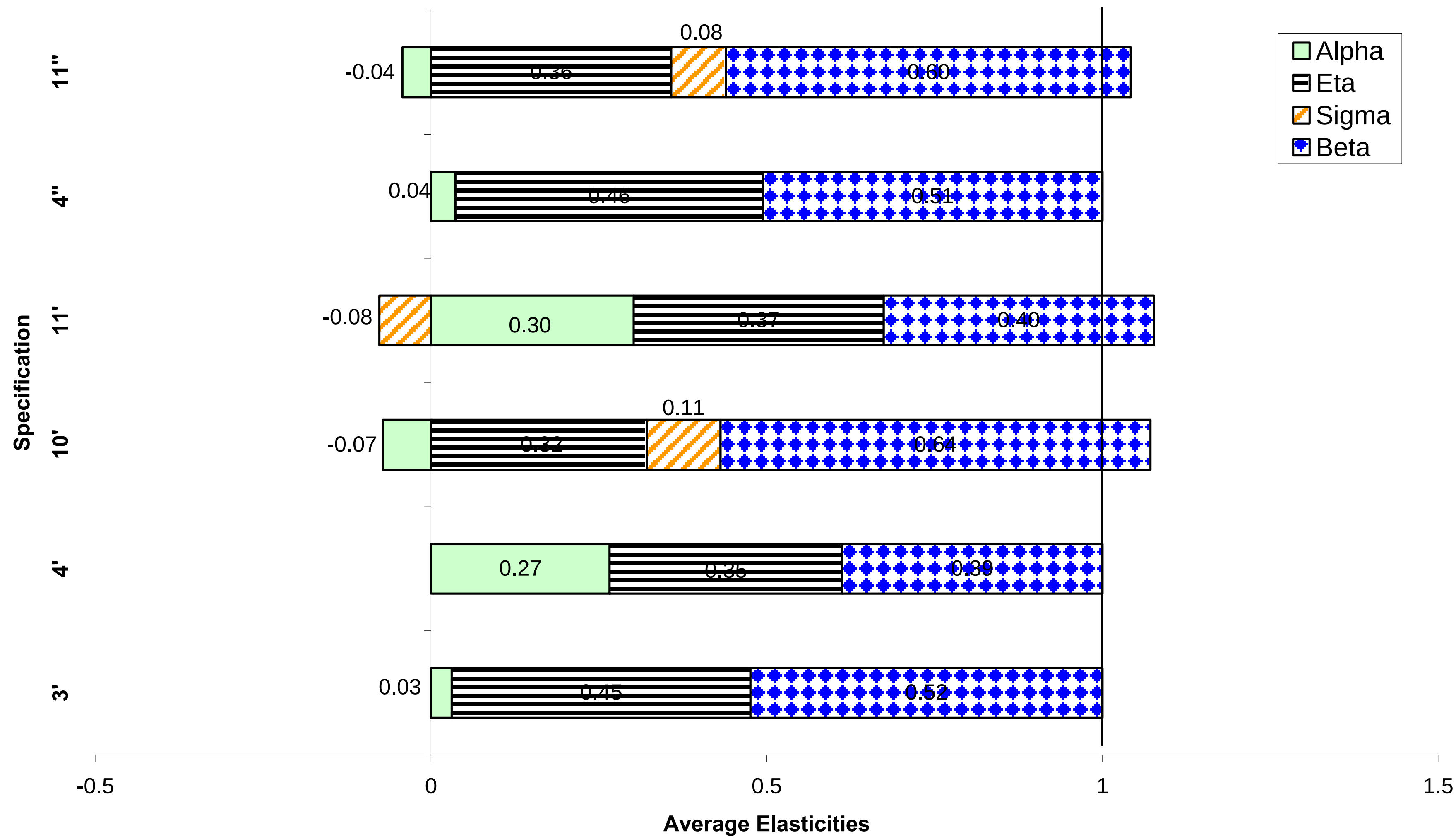
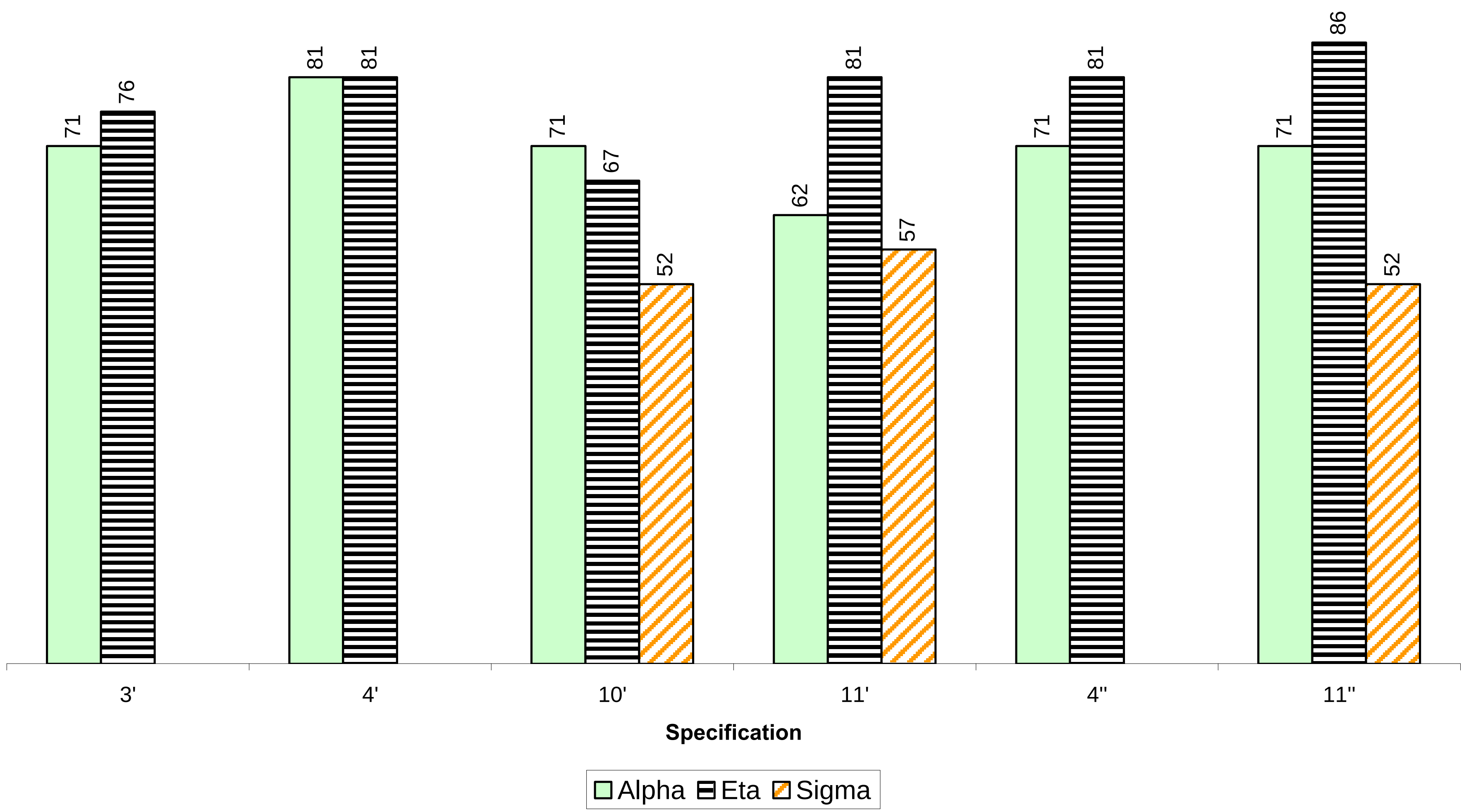


**Figure 4-16, Percent of Elasticities that are Positive -- Specifications Not Including Materials (Nonmanufacturing)**



## Figure 4-17, Average Tau -- Specifications Not Including Materials (Nonmanufacturing)

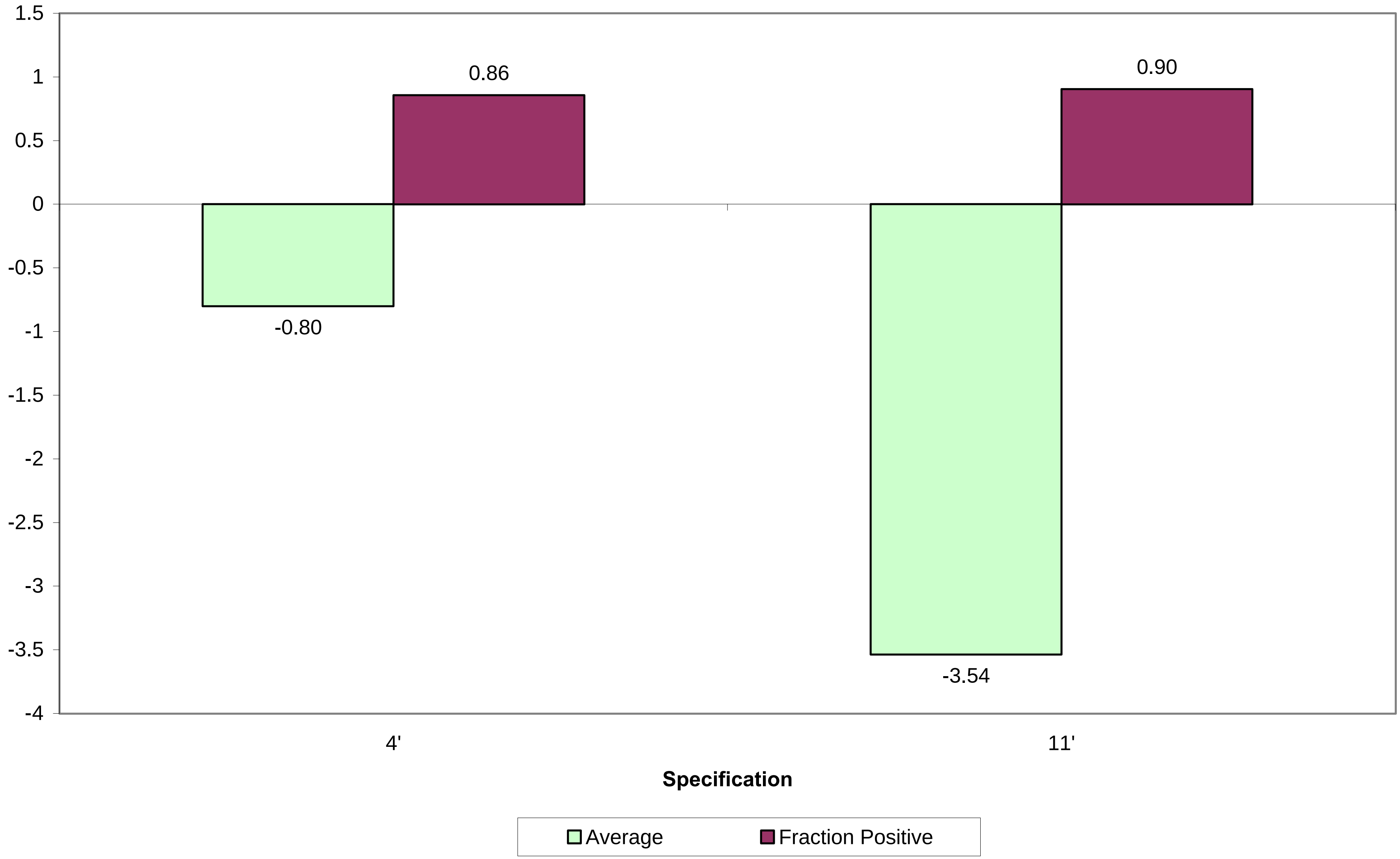


Figure 5-1, Real GDP

Percent Deviations from base -- 2% increase in equipment investment in all years

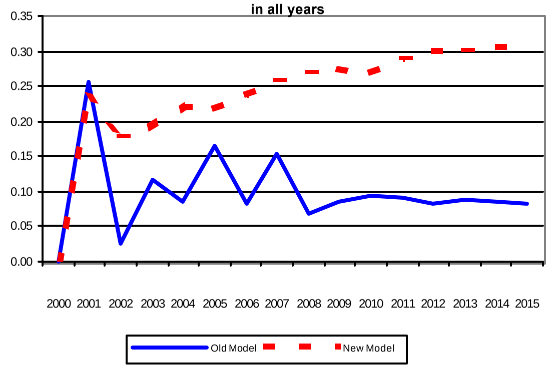



Figure 5-2, Nominal GDP

Percent Deviations from base -- 2% increase in equipment investment in all years

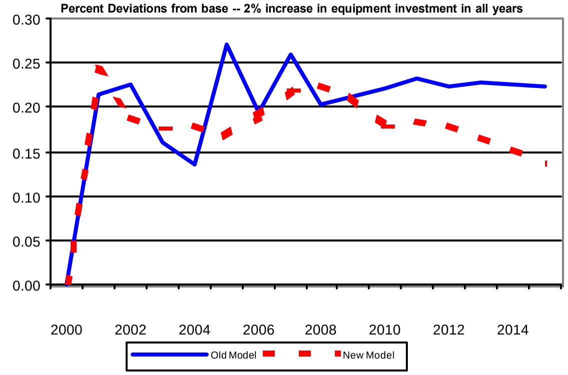



Figure 5-3, GDP Deflator

Percent Deviations from base -- 2% increase in equipment investment in all years

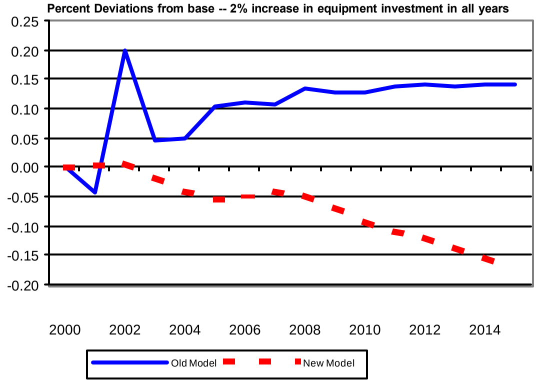



Figure 5-4, Treasury Bill Rate

Level Deviations from base -- 2% increase in equipment investment in all years

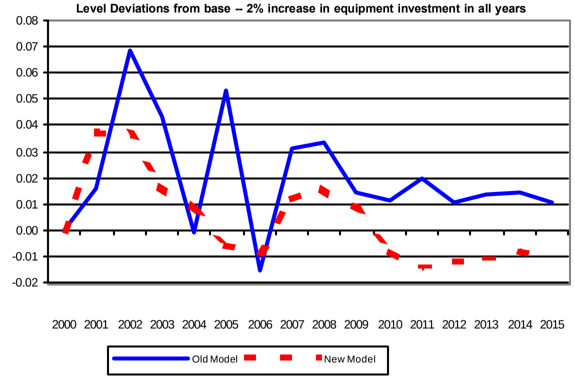


**Figure 5-5, Savings Rate**

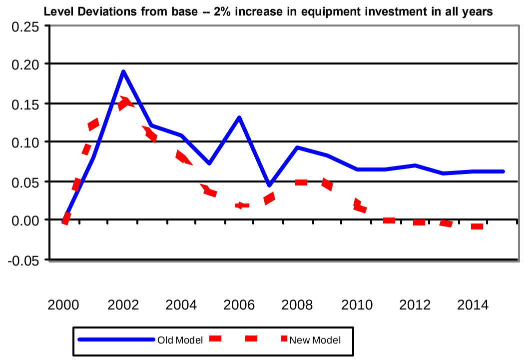



**Figure 5-6, Unemployment Rate**

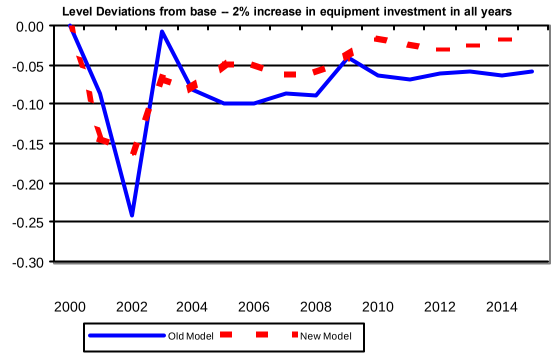



**Figure 5-7, Total Private Employment**

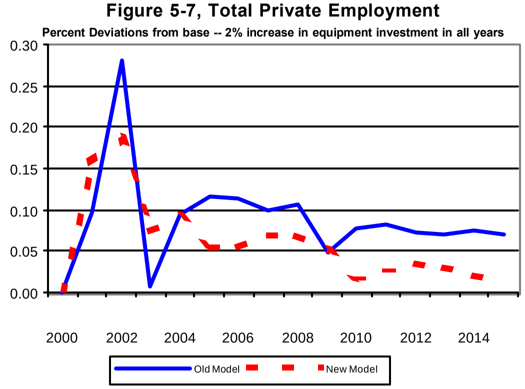



**Figure 5-8, Total Private Hours Worked**

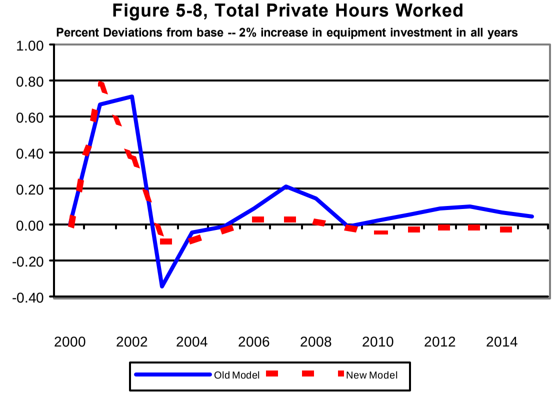


**Figure 5-9, Average Real Wage**

Percent Deviations from base -- 2% increase in equipment investment in all years

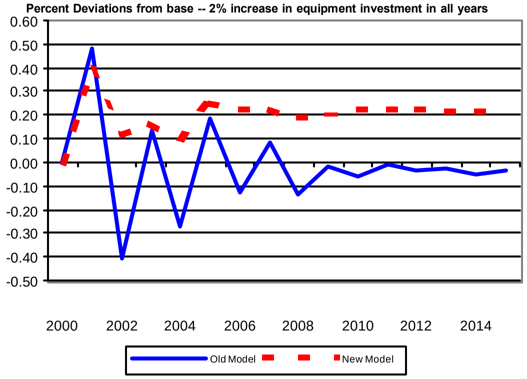
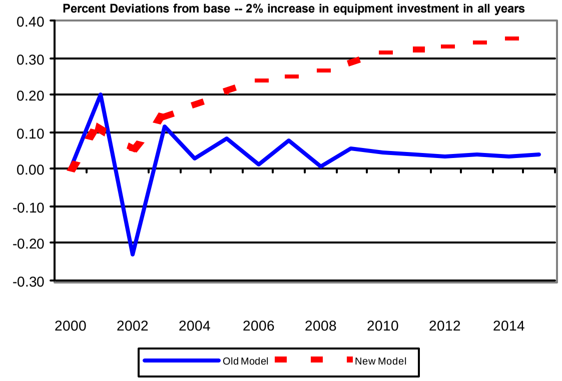


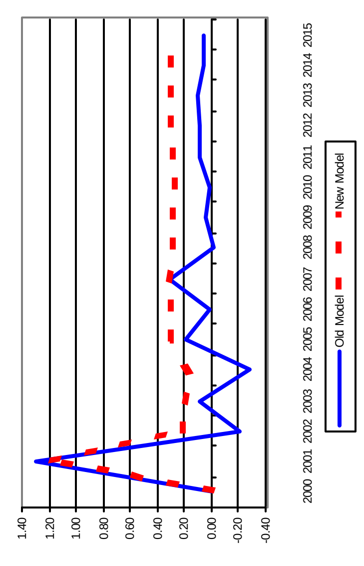

**Figure 5-10, Labor Productivity**

Percent Deviations from base -- 2% increase in equipment investment in all years



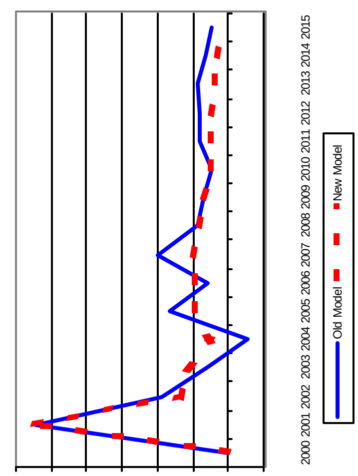
## Figure 5-11, Real GDP

Percent Deviations from base -- 10% increase in equipment investment in 2001



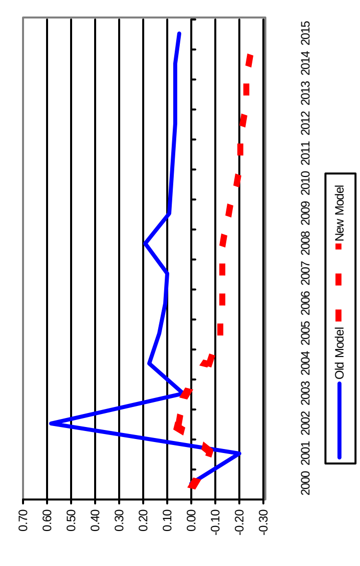

## Figure 5-12, Nominal GDP

Percent Deviations from base -- 10% increase in equipment investment in 2001




## Figure 5-13, GDP Deflator

Percent Deviations from base -- 10% increase in equipment investment in 2001




## Figure 5-14, Treasury Bill Rate

Level Deviations from base -- 10% increase in equipment investment in 2001

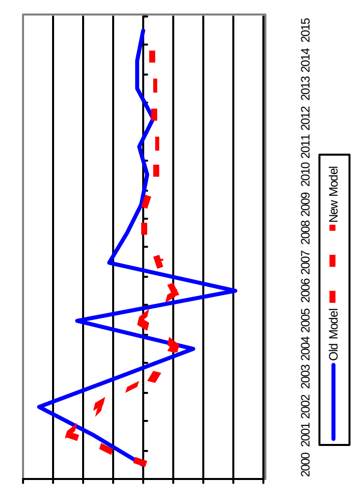


**Figure 5-15, Savings Rate**

Percent Deviations from base -- 10% increase in equipment investment in 2001

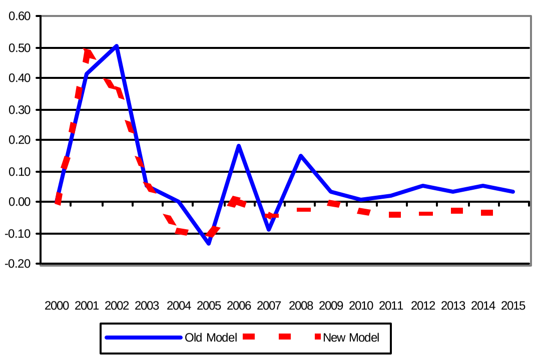



**Figure 5-16, Unemployment Rate**

Level Deviations from base -- 10% increase in equipment investment in 2001

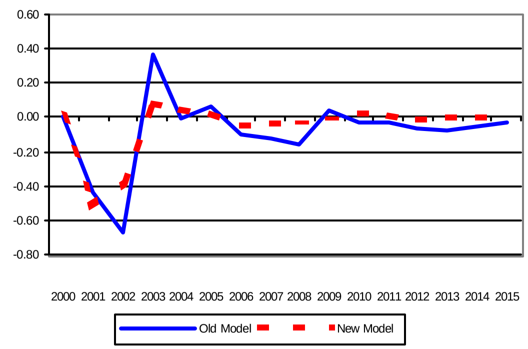



**Figure 5-17, Total Private Employment**

Percent Deviations from base -- 10% increase in equipment investment in 2001

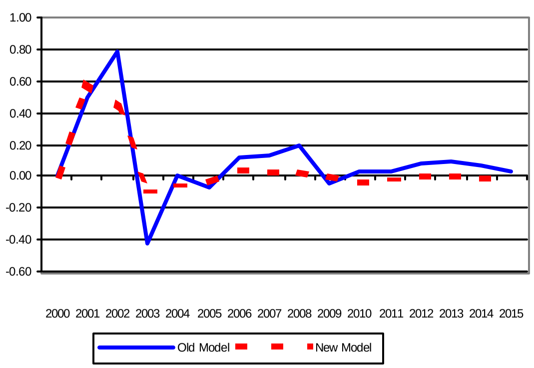



**Figure 5-18, Total Private Hours Worked**

Percent Deviations from base -- 10% increase in equipment investment in 2001

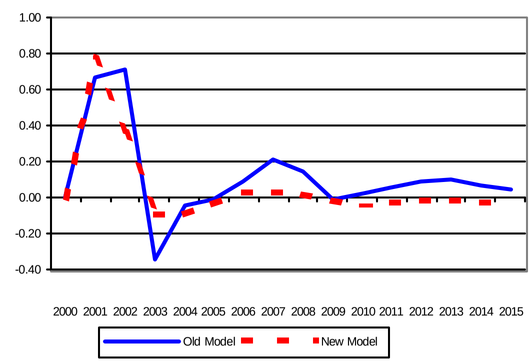


**Figure 5-19, Average Real Wage**

Percent Deviations from base -- 10% increase in equipment investment in 2001

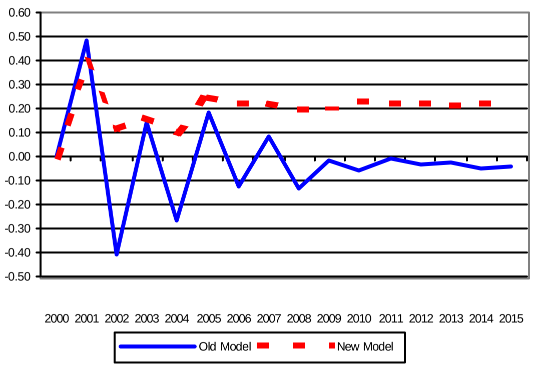



**Figure 5-20, Labor Productivity**

Percent Deviations from base -- 10% increase in equipment investment in 2001

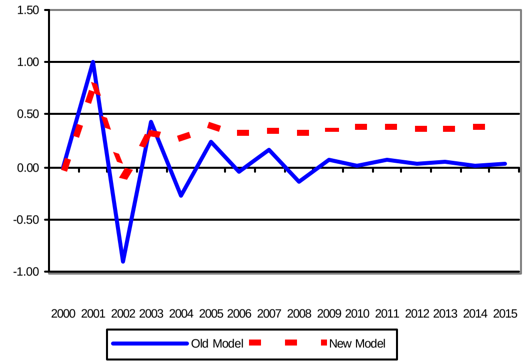



**Figure 5-21, Equipment Investment**
**Percent Deviations from base -- 10% increase in equipment investment in 2001**

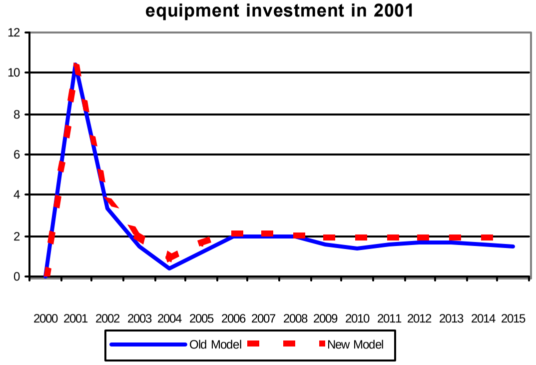



**Figure 5-22, Equipment Capital**
**Percent Deviations from base -- 10% increase in equipment investment in 2001**

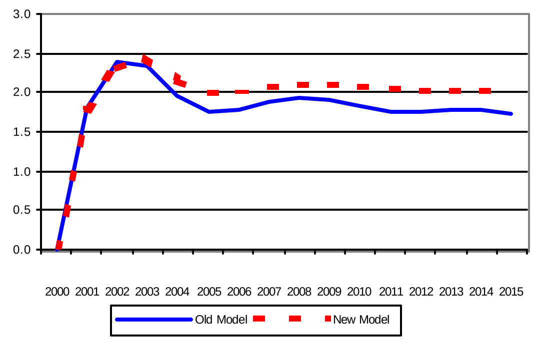


**FIGURE A-1**
**Percentage of All Mfg. Plants In Each Sample**

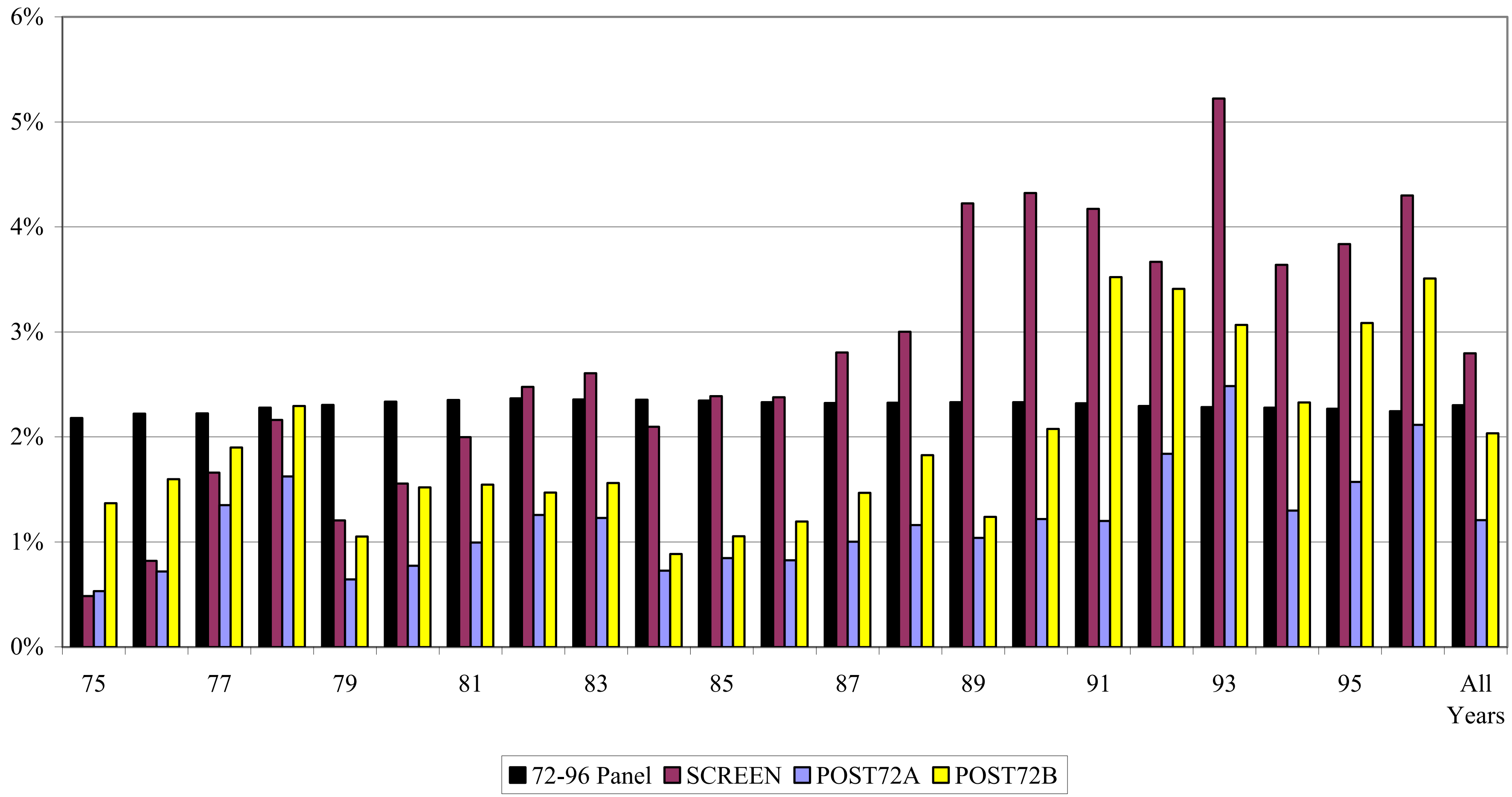


**FIGURE A-2**
**Percentage of Aggregate Mfg. Shipments Accounted For By Each Sample**

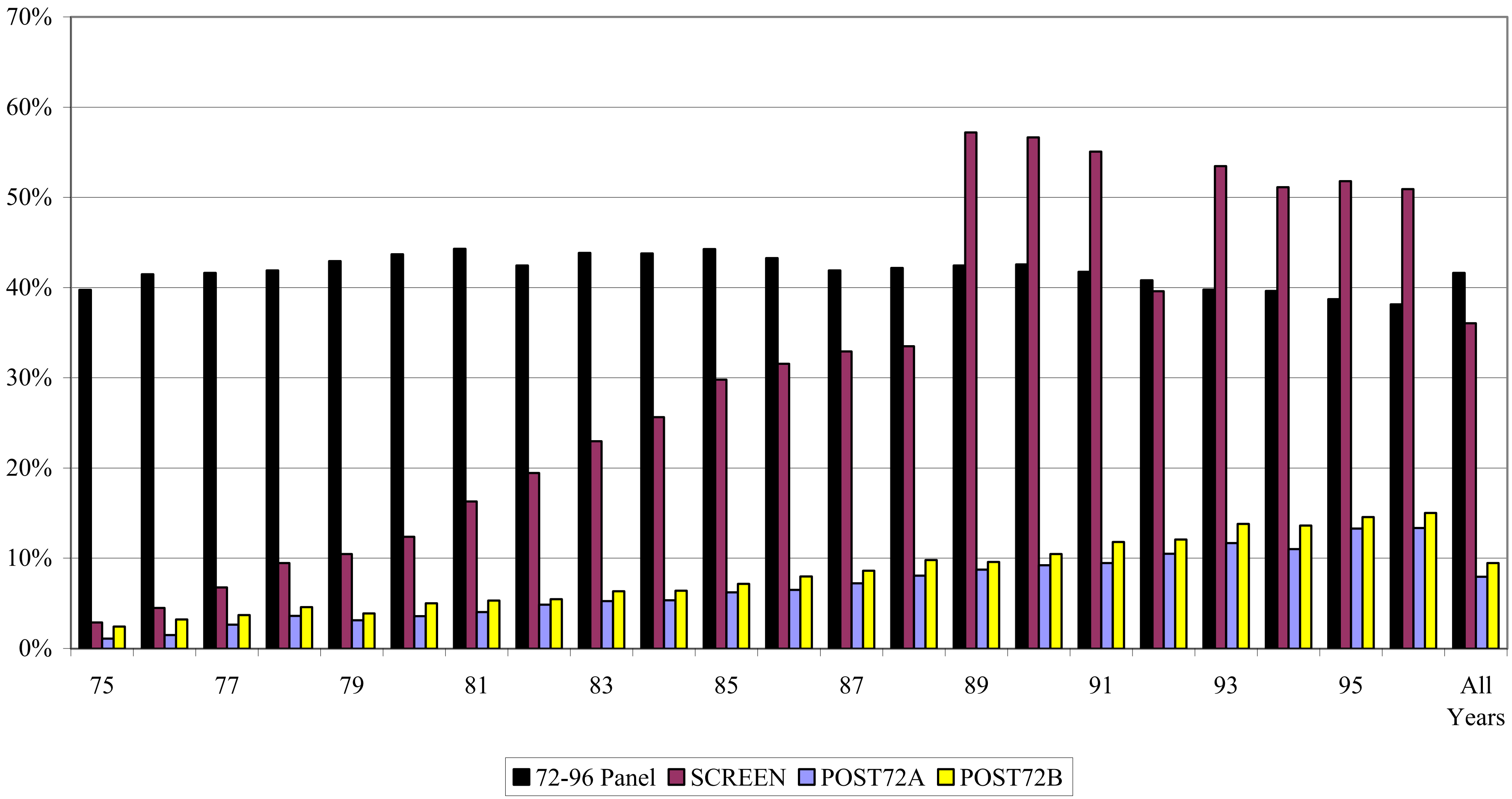


**FIGURE A-3**
**Mean Plant Shipments (in $1000)**

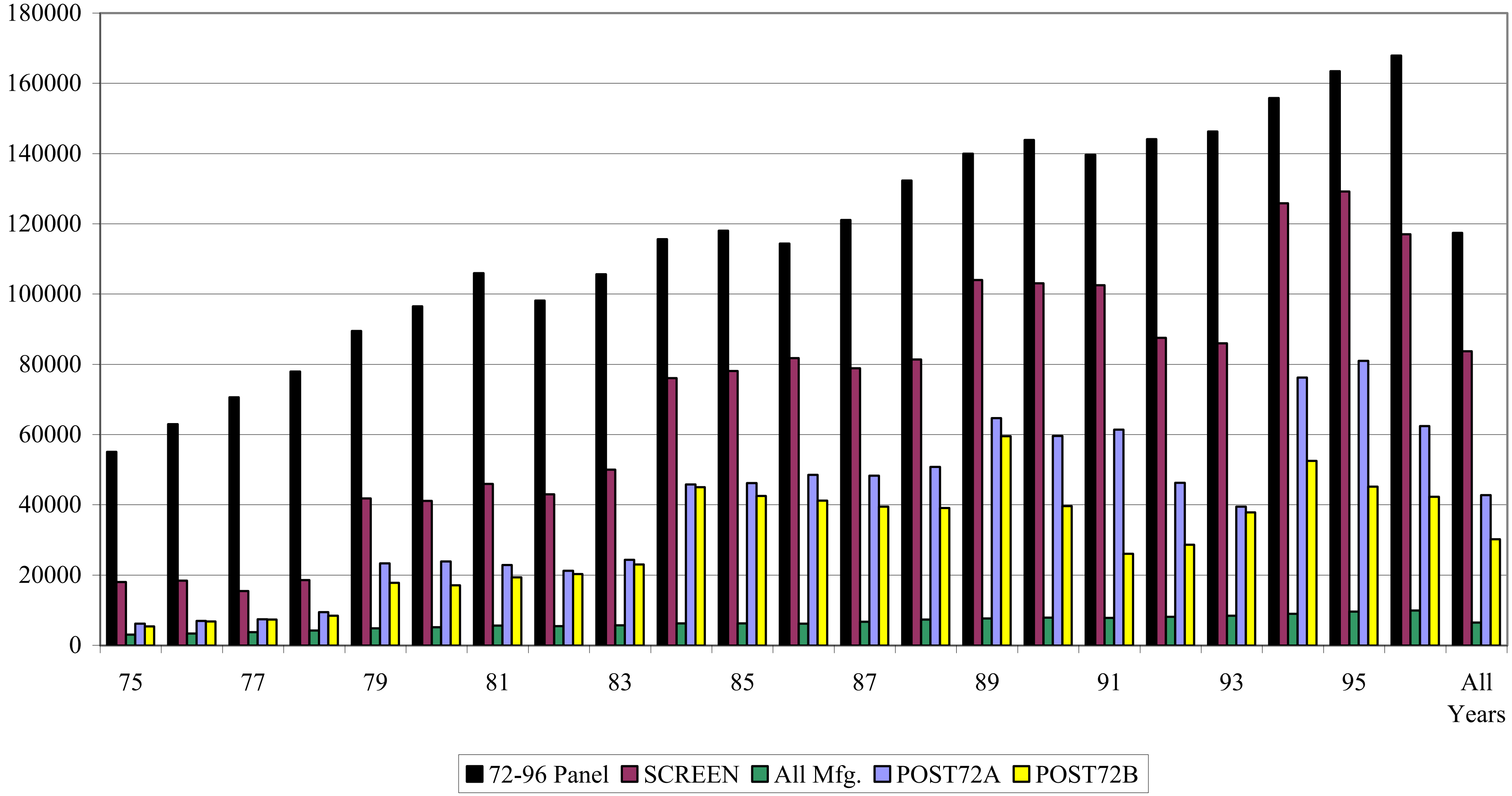


**FIGURE A-4**
**Average Age of Sample Plants By Year**

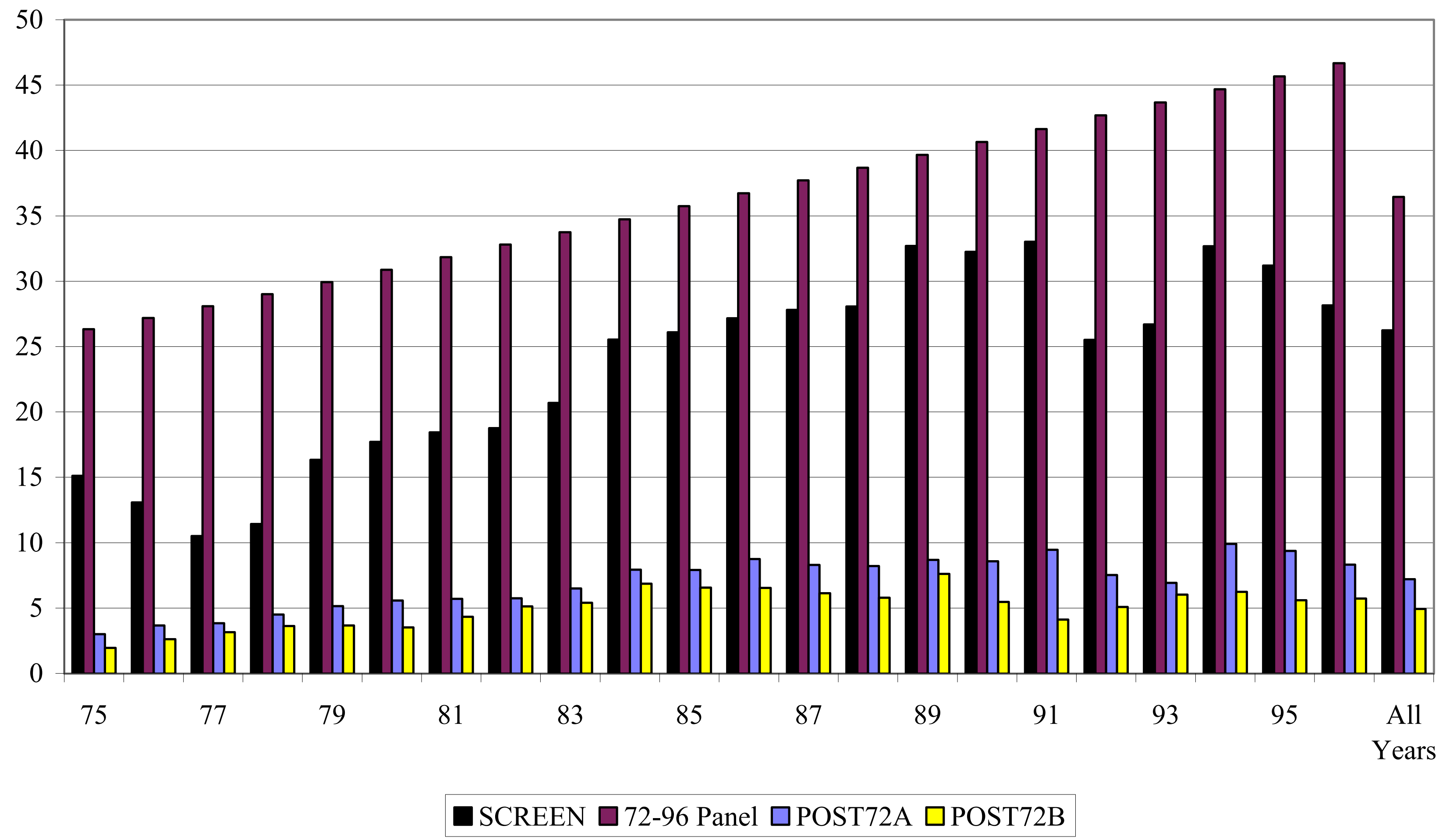


**FIGURE A-5**
**1975-96 Mean 2-digit Industry Shares of Aggregate Mfg. Shipments For POST72A**

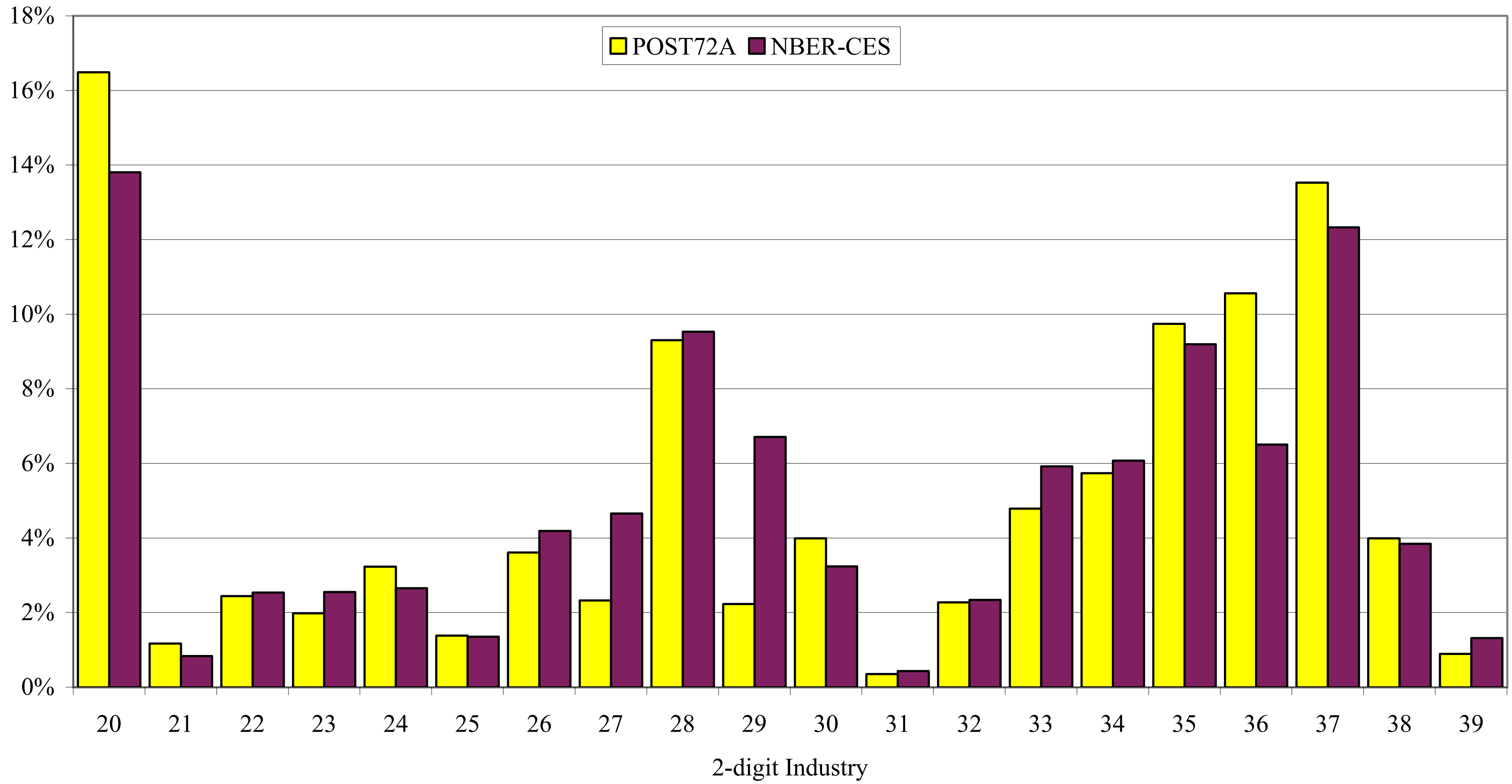


**FIGURE A-6**
**1975-96 Mean 2-digit Industry Shares of Aggregate Mfg. Shipments For POST72B**

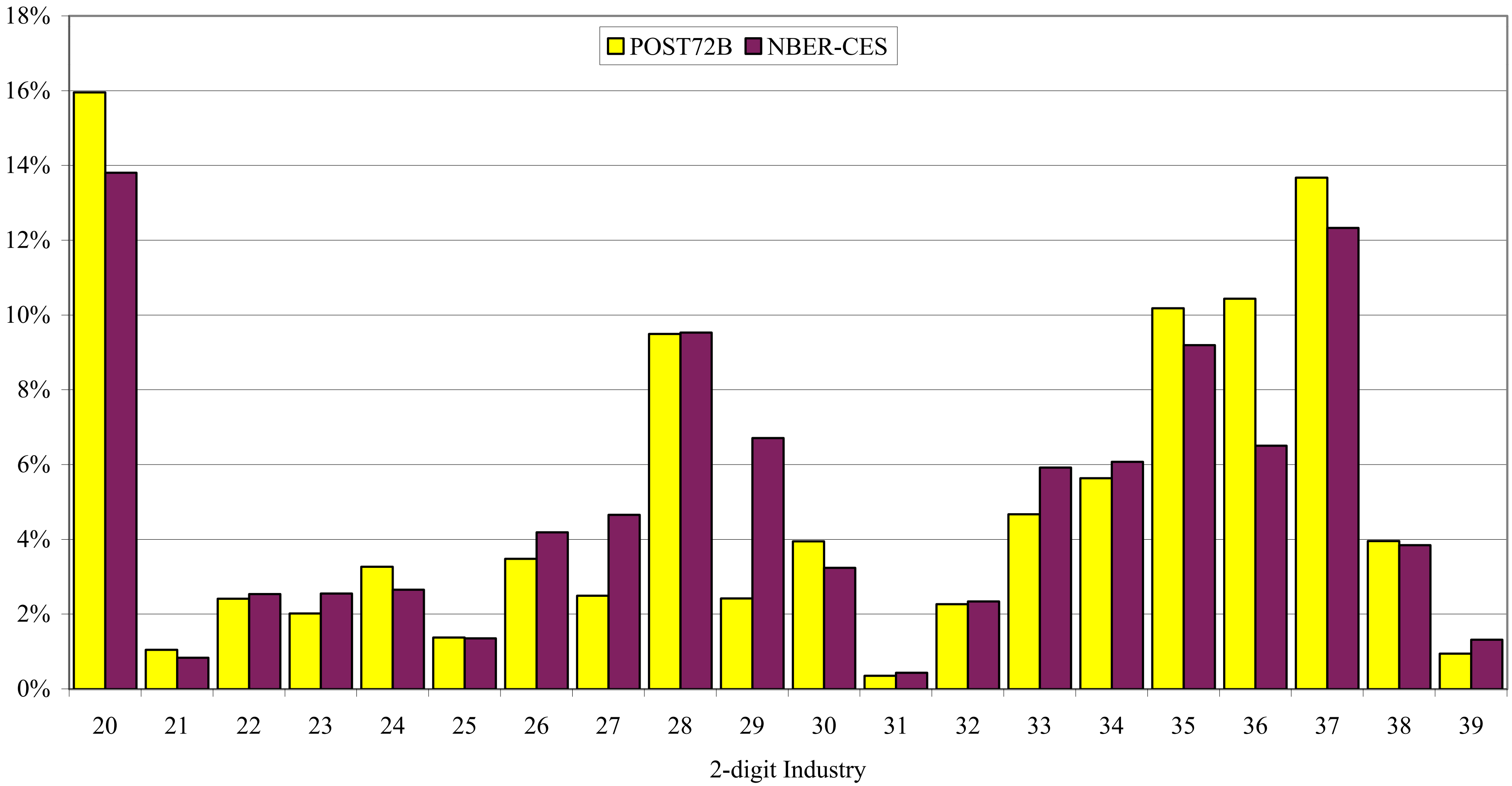


**FIGURE A-7**
**1975-96 Mean 2-digit Industry Shares of Aggregate Mfg. Shipments For 1972-96 Panel**

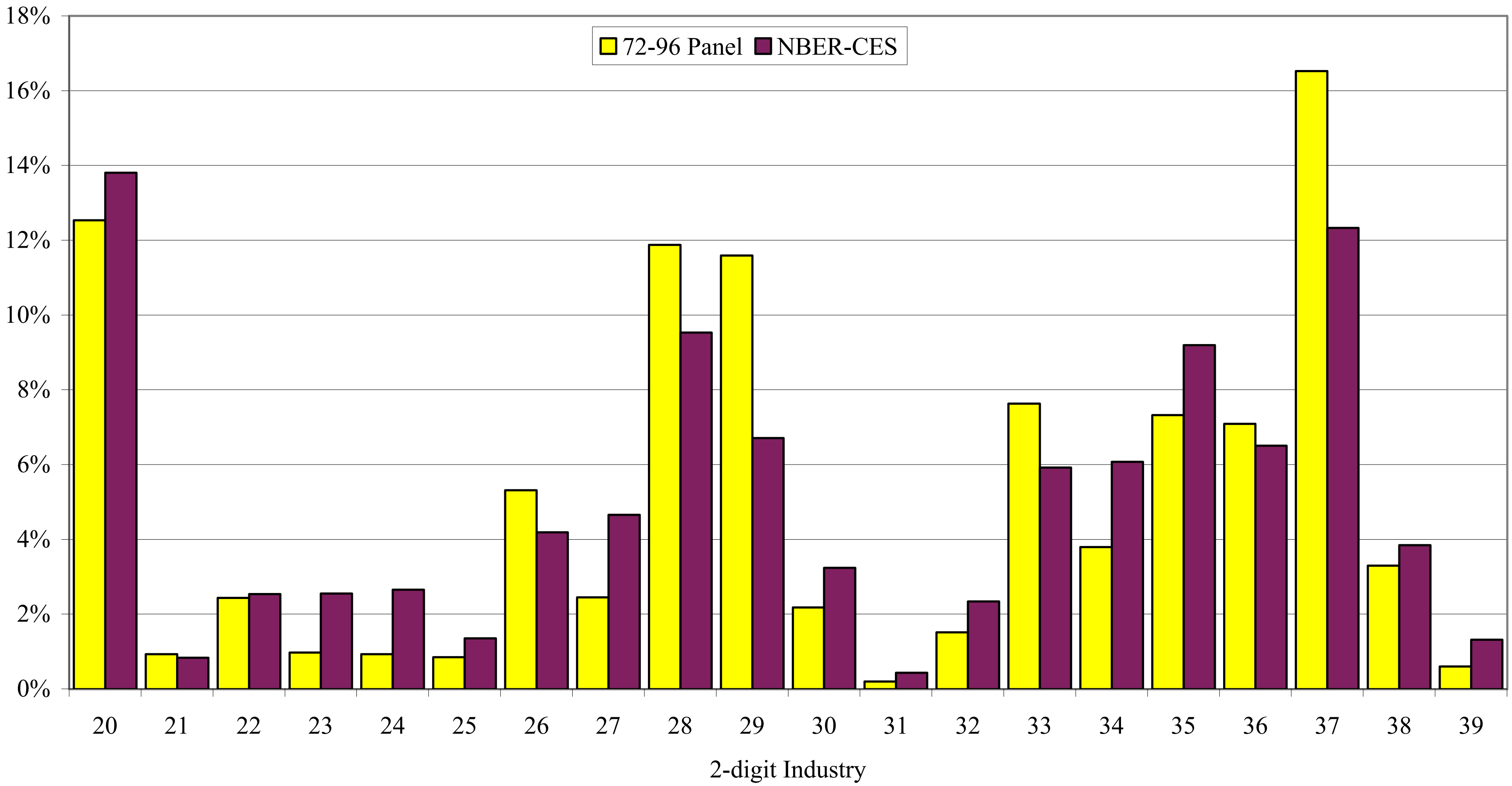


**FIGURE A-8**
**1975-96 Mean 2-digit Industry Shares of Total Mfg. Shipments For SCREEN**

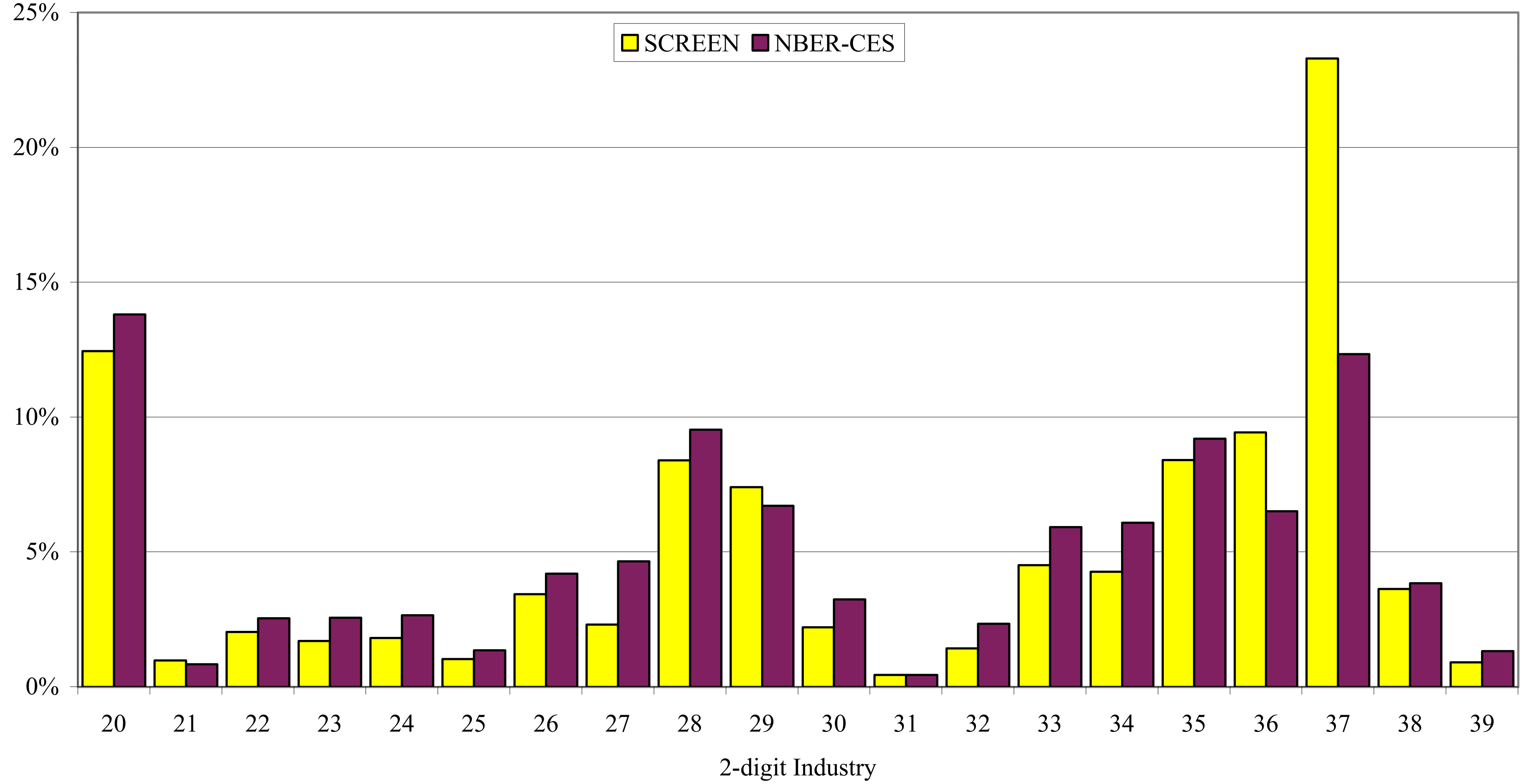


**FIGURE A-9**
**Employment Growth**

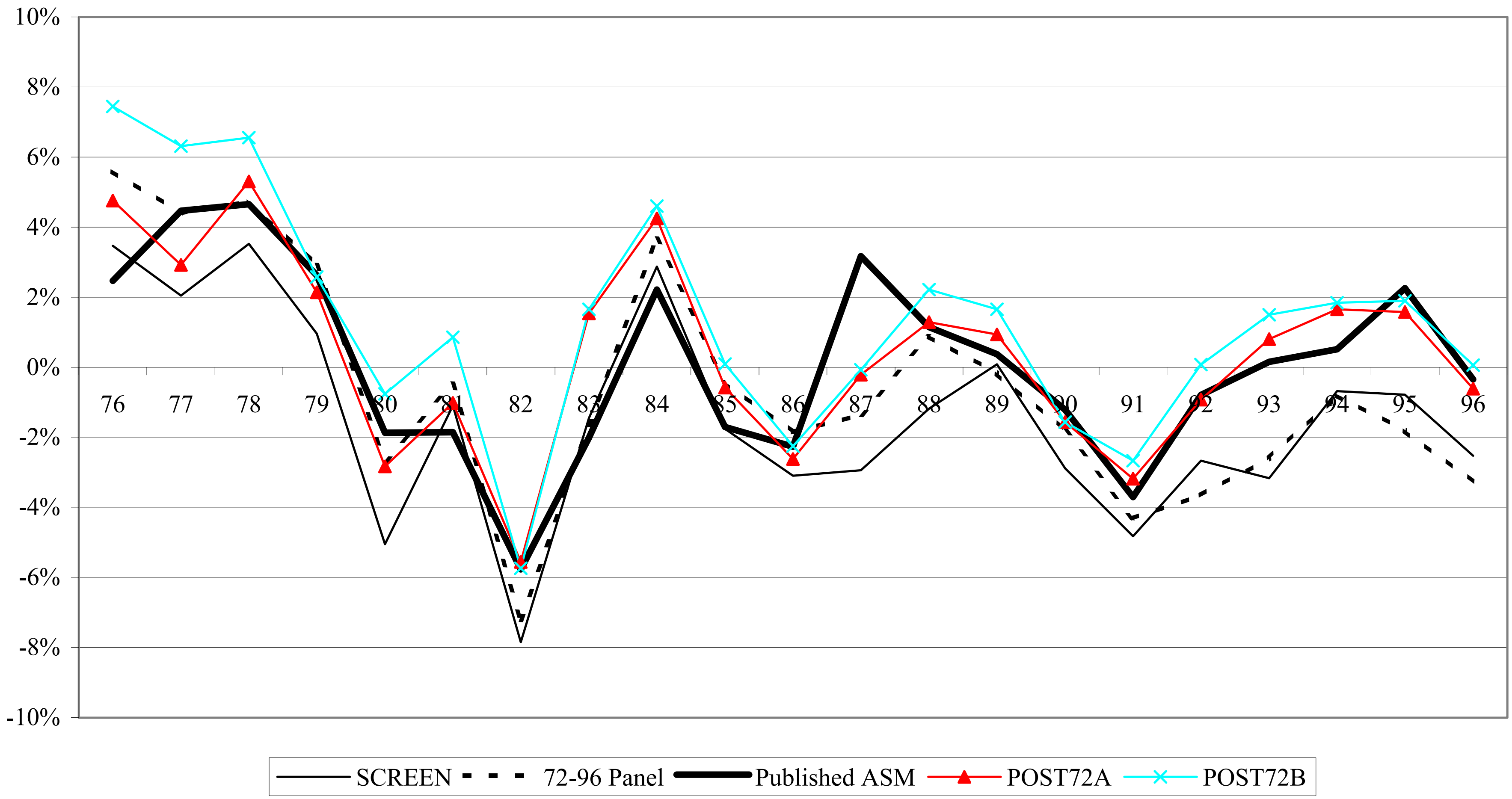


**FIGURE A-10**
**Growth Rates of New (Gross) Investment (Historical $)**