

Quantifying Embodied Technological Change¹

Plutarchos Sakellaris

University of Maryland and University of Ioannina

and

Daniel J. Wilson

Federal Reserve Bank of San Francisco

Abstract:

We estimate the rate of embodied technological change directly from plant-level manufacturing data on current output and input choices along with histories on their vintages of equipment investment. Our estimates range between 8 and 17 percent for the typical U.S. manufacturing plant during the years 1972-1996. Any number in this range is substantially larger than is conventionally accepted with some 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 do not adequately account for quality change. As a result, measured capital stock growth is biased. Third, if accurate, the Hulten and Wykoff (1981) economic depreciation rates may primarily reflect obsolescence.

Keywords: productivity growth, embodied technological change, equipment investment, plant, producer durable price index.

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1. Introduction

Johansen (1959) and Solow (1960) argued that more recent vintages of capital may embody technological advances that make them “better”, or equivalently “of higher quality”, than older vintages. In that case, investment is essential in order to reap benefits from the part of technological progress that is embodied in capital. The distinction between embodied and disembodied technological change is important in analyzing many issues related to long-run standards of living and growth.²

Jovanovic and Rob (1999) show that distortions to investment incentives have a substantially larger effect when technological growth is embodied in equipment. In particular, the taxation of equipment plays a big role in explaining development gaps across countries. Eaton and Kortum (2001) attribute about 25 percent of cross-country productivity differences to variation in the relative price of equipment, about half of which they ascribe to barriers to trade in equipment that inhibit the diffusion of embodied technological change across borders.

The decomposition of technological change to embodied and disembodied may be important for understanding medium-run growth experience, as well. From 1995 to 1999 U.S. labor productivity and total factor productivity (TFP) grew at rates about double those of the preceding 20 years. This dramatic change has led to some important questions. What are the reasons for this productivity surge? Is it going to be long lasting?

A possible explanation for this surge in productivity growth assigns a big role to equipment investment. The U.S. economy experienced an equipment investment boom in the middle and late 1990's. Investment in equipment and software averaged 9.6 percent of GDP

² Throughout this paper we will be using the terms embodied and investment-specific technological change interchangeably.

between 1995 and 1999, 3.2 percentage points higher than the average from 1987-94. Much of this new equipment was for Information Technology but other types of equipment were also purchased en masse. If new equipment embodies technology that is more productive on the margin than that of older equipment and official price indices do not fully reflect such quality changes then an equipment investment boom should be accompanied by an increase in measured TFP growth. TFP will grow faster than average for as long as the rates of investment are heightened.

There is another possibility for sustainably high TFP growth rates within this framework. If the rate of growth of technology that is embodied in new vintages of investment has increased then at any rate of equipment investment measured TFP growth will be higher.³ Some have argued that the advent of Information Technology (the computer revolution) and its incorporation into production has slowly pushed the average rate of embodied technological change higher (see Greenwood and Yorukoglu, 1997, among others).

A serious shortcoming in the above discussion has been the lack of reliable estimates of the rate of technological change that is embodied in equipment capital. Most of the literature on embodiment, including the papers of Hulten (1992) and Greenwood, Hercowitz, and Krusell (1997), has relied on an estimate of about 3 percent for the years 1954 to 1990. This estimate was derived by comparing the rates of growth of either a consumption deflator or the official price index for equipment investment (which turn out to be quite similar) with another one constructed by Gordon (1990), which is intended, *inter alia*, to capture change in the quality of new vintages of equipment. However, as Gordon (1996) points out, the difference in the growth

³ Again it is important for this argument to go through that official price indices do not incorporate quality growth adequately.

rates of his index and either of the other two is not due to quality change alone. Furthermore, not all kinds of quality change are captured by the Gordon (1990) index.⁴

In this paper, 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, after 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 complete history of investment in equipment by vintage, 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). This number is astounding compared to the commonly accepted 3 percent based on Gordon's (1990) series.⁵ We evaluate the impact of embodied technological change on US manufacturing productivity 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 total technological change was about two thirds. These findings have several important implications. First, the role of investment-specific technological change as an engine of growth is even larger

⁴ See Section 3 for further discussion on the use of Gordon's index to capture embodied technological change.

⁵ A notable exception is Bahk and Gort (1993) who also estimate a high rate of embodied technological growth.

than previously estimated. Second, existing producer durable price indices substantially mismeasure quality change, yielding downward 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 the average capital asset's value over time.

2. A two-sector model of investment-specific technological change⁶

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:

$$\tilde{i}_t = z_t q_t \tilde{k}_{\tilde{i},t}^\alpha l_{\tilde{i},t}^{1-\alpha} \quad (1)$$

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

where z is the level of technology common to both sectors whereas q is technological level specific to the investment sector⁷. A “~” denotes that the variable is defined in terms of

⁶The 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.

⁷Greenwood et al. (1997) discuss conditions under which the economy exhibits balanced growth with or without exogenous technological change.

efficiency units. For simplicity, α , the elasticity of output with respect to capital is assumed to be the same in both sectors.⁸ 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 rate of growth of investment-specific

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

Figure 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 types⁹. Oddly enough, these two indexes grow about the same rate between 1972 and 1996¹⁰.

⁸Hornstein and Krusell (1996) show the implications of allowing α to differ by sector.

⁹The 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.

¹⁰The average growth rate of the PCE deflator is about 5.3% per year. The equipment-investment price index grows at about 5.1% per year and is very similar to the deflator for "Industrial Equipment" in NIPA, which grows at 5.5% per year. It is interesting to note that the two price indices in Figure 1 display distinctly different behavior 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.

Does this mean that there was no embodied technological change during this period? Several authors provided a negative answer arguing that the official price indexes for PDE grow too fast as a result of mismeasurement. These authors use, instead, equipment-investment price indexes constructed by Gordon (1990) to reflect quality change. The drop in the price of equipment (relative to the PCE deflator) suggested by Gordon's index implies a rate of embodied technological change of 3.2%. 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 .

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:

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

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

$$\tilde{k}_t = (1 - \delta) \tilde{k}_{t-1} + i_t q_t \quad (4)$$

where δ is the geometric rate of physical depreciation¹¹. In order to construct the capital stock correctly one needs to adjust each vintage of investment for quality change that is due to

¹¹This concept comes in many other names, for example, physical decay, or depreciation from use. It is not equivalent to economic depreciation, which includes the effect of obsolescence as well.

investment-specific technological change. 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.

A new method to identify q :

Equations (3) and (4) suggest an alternative way to 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. There are four important elements to this approach:

- 1) Deflate output and investment by a price index that does not adjust for quality change.
- 2) Apply depreciation adjustments to capital that capture physical deterioration but not obsolescence.
- 3) Allow the marginal productivity of each vintage to be freely estimated.
- 4) Use the estimated residual to identify disembodied technological change.

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.

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 single aggregate index from 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 effect 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 1990¹².

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 1973¹³. They argue that increased technological change and the adjustment processes necessitated by it are largely responsible for the post-1973 measured slowdown in productivity growth. 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 the 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.¹⁴

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_{z_t} in our two-sector model) and do not

¹² Disembodied change provided the rest. The authors actually use the terminology investment-specific versus neutral technological change.

¹³ This increase is about 25 percent. See, e.g., Hornstein and Krusell (1996) p. 231.

¹⁴ There are several related papers. See Greenwood et al. (2000) pp. 110-2 for a partial review.

necessarily represent an increase in technology.

Finally not all kinds of quality change are captured by the Gordon index. Gordon was only able to create new price indices for durable goods for which sufficient data on model characteristics and prices existed. The Sears catalog was the primary source of this data. For a large number of goods there simply was no data.¹⁵ Given these problems, it seems fruitful to examine alternative methods of estimating embodied technological change.

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 (k) is proportional to a time trend *plus* the difference of γa_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

¹⁵Gort and Wall (1998) argue that estimates of embodied technological change based on Gordon (1990) may be biased substantially 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.

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 depreciation¹⁶. Their estimates are best regarded as describing the joint impact of physical depreciation and embodiment. Our view is that physical decay occurs at a rate higher than zero.

A recent paper by Hobijn (2001) is an interesting addition in this strand of the literature. Using data for 4-digit US manufacturing he estimates the rate of embodied technological change from an equation derived from the investment Euler equation. He finds estimates that average about 12 percent. As we will see in Section 6, this is remarkably close to our preferred estimate for US manufacturing.

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

¹⁶While they admit that “this assumption is only at best an approximation of reality” (p.566) they do not provide concrete supporting evidence for it.

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 & Dunne (1998) 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 synchronized across plants.

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

$$y_{it} = \beta \cdot l_{it} + \theta \cdot m_{it} + \alpha \cdot \log(U_{it}^P J_{it}) + \eta \cdot \log(U_{it}^S S_{it}) + \zeta_{it} \quad (5)$$

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 year¹⁷. Lowercase letters denote natural logs. The disturbance term, ζ_{it} , captures stochastic shocks to disembodied technology. It may contain both an aggregate and an idiosyncratic component. Equation (5) is the plant-level analogue of aggregate production function (3).

The variables U^J and U^S in equation (5) denote 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

¹⁷All variables are in constant dollars unless stated otherwise.

assume:

$$U^J = (E/J)^{\frac{1}{\tau_J}} \quad \text{and} \quad U^S = (E/S)^{\frac{1}{\tau_S}} \quad (6)$$

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 (5) and rearranging, we obtain

$$y_{it} = \beta \cdot l_{it} + \theta \cdot m_{it} + [\alpha(\tau - 1)/\tau] \cdot \log(J_{it}) \\ + [\eta(\tau - 1)/\tau] \cdot \log(S_{it}) + [(\alpha + \eta)/\tau] \cdot e_{it} + \zeta_{it} \quad (7)$$

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).¹⁸

In this paper, 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 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):

¹⁸A data appendix describing the construction of each of the variables and containing a description of the properties of our samples can be provided by the authors upon request.

$$J_t = \sum_{s=1}^T I_{t-s} D_{t,t-s} \phi_{t-s} \quad (8)$$

where T is the age of the plant, I_{t-s} is real equipment investment of vintage $t-s$ capital goods, $D_{t,t-s}$ is the fraction of one dollar's worth of vintage $t-s$ investment that is still used in production in year t , and ϕ_{t-s} is the level of embodied technology in equipment capital of vintage $t-s$ relative to some numeraire year's technology^{19 20}. This equation is analogous to equation (4) in the 2-sector model. Equation (8) 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 equipment²¹.

Substituting equation (8) into (7) 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 ϕ_{t-s} was not possible in all but the most parsimonious of specifications. Thus, for the regressions reported in this paper, we simplify by assuming a constant geometric rate of embodied technological change. This changes the specification of J to:

¹⁹ In terms of the two-sector model we described earlier, ϕ_t is the ratio of q_t to q_0 where 0 refers to the numeraire year.

²⁰ 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).

²¹ 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 γ are uniformly higher under this specification.

$$J_t = \sum_{s=1}^T I_{t-s} D_{t,t-s} (1 + \gamma)^{t-s-t_0} \quad (9)$$

where γ 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.²²

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 use²³. The parameter τ in the assumed functional form (6) is the elasticity of the rate of energy use with respect to capital utilization. It 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.

²²Equations (8) and (9) 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.

²³ This approach was suggested by Jorgenson and Griliches (1967) and followed by Burnside et al. (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.

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.²⁴

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 (see Mohr and Gilbert, 1996).

There are two important differences. First, the FRB-BLS methodology results in an age-efficiency schedule that is substantially different from geometric, especially in the early part of an asset's life. Second, the implied rate of depreciation is lower than that for BEA. These features can be seen in Figure 2 which graphs the average 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 (8)²⁵. The same is done for the $D_{i,t,t-s}$ data that is implied by the BEA

²⁴Petropoulos (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 ($\tau > 1$).

²⁵Though $D_{i,t,t-s}$ has a plant subscript, empirically this variable is the same for all plants within a 3-digit industry.

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 robustness of our estimates of γ to 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 quinquennial Census of Manufactures (CM) and the Annual Survey of Manufacturing (ASM). At the time of this writing it covers 1963, 1967, and 1972-96.

We construct several data samples with which to estimate equation (3).²⁶ Our primary 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 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

²⁶ We will report results for our primary sample only. Results using other samples are available from the authors upon request.

different vintages of investment. An alternative sample was constructed in order to test the robustness of our results to the possibility of sample selection bias introduced by the exclusion of plants born prior to 1972. The results are robust to this change of sample (results from alternative samples are available from authors upon request).

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 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 in the LRD 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. Using an alternative sample that retained observations of two- and three-year old plants, we found that our results do not appear to be biased by their exclusion (alternative sample results available from authors upon request).

Is our Sample Representative of Manufacturing?

Our primary sample consists of a total of 96,846 plant-year observations covering 24,404 plants. We performed a detailed comparison of this sample to the other samples we use and to the aggregate manufacturing sector (the results of which can be provided by the authors upon

request). 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 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, γ , 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.²⁷

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 τ is 2.08 (with a 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)²⁸.

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

²⁷Allowing factor elasticities to vary by industry yields a slightly lower estimate of γ 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.

²⁸For plant-level evidence on these patterns of correlation see Sakellaris (2000).

estimate of γ is much higher now at 17 percent. This implies a vastly higher rate of embodied technological change than is usually considered.

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.”²⁹ Ignoring such learning effects might bias our estimate of γ , 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.³⁰ 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 1, the estimate of γ is about 12 percent and the rest of the coefficients do not change much.³¹

Average Vintage Effect

²⁹See Greenwood and Jovanovic (1998) for an extensive analysis of the macroeconomic implications of learning-by-doing as well as references to some recent work.

³⁰ We identify a spike with observations of equipment investment to capital ratios greater than 0.20. See Power (1998), Doms and Dunne (1998), Cooper et al. (1999) and Sakellaris (2000) for justification of using this definition at the plant level.

³¹The coefficients on the spike indicators show an approximately 6% drop in productivity in the first year after a spike with slow recovery thereafter.

In Section 3 we mentioned that an alternative production-based approach which obtains γ via the estimated coefficient on average age or vintage is due to 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):

$$y_{it} = \rho \cdot t + \beta \cdot l_{it} + \theta \cdot m_{it} + \eta \cdot s_{it} + \alpha \cdot j'_{it} + \alpha \cdot \log(1 + \gamma \bar{V}_{it}) \quad (10)$$

where j' is log equipment capital unadjusted for embodied technological change (i.e. j' is just j from equation 14 with γ set equal to zero) and \bar{V} is the average vintage of equipment for plant I in year t . Generally, $\gamma \bar{V}$ is assumed to be close to zero allowing the last term in (10) to be approximated by $\alpha \gamma \bar{V}_{it}$. 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 γ , say 0.01, will still be far from zero suggesting that serious specification errors are likely when we estimate (10).

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

Industry heterogeneity

One concern we have is that the 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 included a set of industry-specific time trends in each of our regressions. All industry trends were estimated between ± 1 percent with the important exceptions of computers (8.3%) and communication equipment (3.3%).³² 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 γ . 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.

Time variation in the parameters

One may also be concerned with whether γ has varied greatly over time. To test this, we estimate our full specification allowing γ to vary by year and test the hypothesis that γ 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 γ over cross-sectional years.

Another concern is whether our pooled estimate of γ is affected by the assumption that the elasticity of energy usage with respect to capital utilization, τ , is constant. It is possible that τ was higher 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, $\alpha(\tau-1)/\tau$, is increasing

³²These 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.

in τ . If estimated τ is constrained to be constant whereas, in reality, it was higher early on then the contribution of early vintage equipment to output would be understated. To compensate, OLS will tend to overweight early vintage investment relative to later investment in order to minimize SSE. This implies a downward bias in $\hat{\gamma}$ when constraining τ to be constant. However, allowing τ 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 1, Column C. Furthermore, τ_t does exhibit a slightly rising trend over time, which is statistically significant according to a Wald test.³³

Alternative Depreciation Assumptions

The estimate of γ depends on the assumption for physical depreciation. We now 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 assuming that physical depreciation is a constant fraction of the BEA-provided rate for each observation's industry and year. We then estimate how γ varies.

Table 3 and Figure 3 contain the results. As expected, the lower is the assumed depreciation rate the higher is the estimate of γ , which ranges from 0 to 25 percent (with standard errors ranging from 4 to 6 percent). Clearly as we allow less of the decrease in productivity of early vintages of investment over time to be explained by physical decay, γ is left to explain more of this decrease. Total economic depreciation, the sum of physical decay and obsolescence, ranges from 13 to 25 percent. Also shown in Figure 3 is the average BEA

³³The F-statistic for the test of the null hypothesis that τ is constant for all years is $8.48 > F_{J,T-K}(.95)=1.00$.

economic depreciation rate of 12% and the implied rates of obsolescence as the physical depreciation rate is increased.

To conclude, even with geometric physical depreciation the estimated rate of embodied technological change is high except in the case where the BEA rates are assumed to reflect physical depreciation and no obsolescence. It is straightforward to show theoretically that in the latter case one excludes the possibility of embodied technological change by assumption.³⁴

Simultaneity Bias

It is well known that OLS estimation of production function relationships is subject to potential simultaneity biases³⁵. 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

³⁴Deflating by the equipment-investment deflator instead of the PCE deflator and repeating the estimation does not change our conclusions.

³⁵ 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.

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 Productivity Database and 2-digit equipment and structures rental rates from the BLS). This leaves in some cases γ , and τ as the only parameters to be estimated.

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 (2001). 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).³⁶

The results of these regressions are shown in Table 4. 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 are measured by their industry cost shares and no utilization adjustment is made.³⁷ Column C contains results from an average vintage specification also without a utilization adjustment and with all factor elasticities measured by cost shares.

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 γ . Yet, despite this apparent relevance, we are not able to estimate γ with any reasonable degree of precision. Of the three regressions shown, only the estimate of γ 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 γ .

Why do we not use the Olley and Pakes (1996) method?

³⁶It 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.

³⁷The iterative estimation procedure was not able to converge when τ was included in the regression.

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 capital stock. This allows productivity to be expressed as an inverse function of investment and capital stock.

Unfortunately, this approach is not appropriate for our model, which allows for 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 5, 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.³⁸ For both our primary plant-

³⁸For 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 γ . 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 (14). Choosing a numeraire year at the beginning of our sample ensures that the growth rate will increase with γ .

level sample and for the aggregate manufacturing data (from BEA), we calculate the annual growth rate of equipment capital stock under six different sets of assumptions.³⁹ The growth rate of the stock implied by the results from our main regression (Column C of Table 1), with $\gamma=0.116$, is 14.7 percent in our sample and 14.0 percent in the aggregate data. 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-Wyckoff rates), which is 4.2 percent in our sample and 3.0 in the aggregate. It is also far above the growth rates of the capital stocks endorsed by either Hulten (1992) or Greenwood, et al. (1997). The key element that generates the higher growth rate in our capital stock construct is the value of γ . When we set γ 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 in our sample and 2.1 in the aggregate.

What is the relative importance of embodied and disembodied technological change for productivity growth in our sample of U.S. manufacturing plants? According to equation (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.⁴⁰ Correspondingly, the rate of output growth that is due to embodied technological change is equal to the equipment elasticity times the differential growth

What is important for comparing capital stock growth rates using different γ 's is not necessarily the sign of this derivative, but just that the derivative is monotonic in γ .

³⁹ Specifically, we regress the log of equipment capital stock on t and an intercept. The coefficient on year gives the average annual growth rate.

⁴⁰ This number is the coefficient on time in a regression of the log of TFP, constructed using the equipment capital stock with a $\gamma=.116$, on time and an intercept.

rate of quality-adjusted and non-quality adjusted equipment capital stocks. This measure averages 1.17 percent annually in our sample.⁴¹ 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

Assessing the rate of embodied technological change is of high importance. It is a necessary ingredient for productivity analysis and for constructing 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 paper, we develop a production-side approach that provides alternative estimates of embodied technological change without relying on accurate measurement of price indices for producer durable equipment. We find that the rate of embodied technological change is between 8 and 17 percent with our preferred estimate being 12 percent. These rates are much higher than that captured by the relative rate of decline of Gordon's (1990) equipment price deflators which puts it no higher than 4%. Our results are consistent with arguments made by Hornstein and 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

⁴¹ The equipment elasticity is 0.114 from Column C of Table 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 estimate in Row A of Table 6 from the 4.4 percent estimate in Row C.

two-thirds of the total growth in TFP of manufacturing plants between 1972 and 1996, suggesting an important role for investment in spurring productivity growth above and beyond its traditional role of capital deepening.

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Table 1

Parameter	A	B	C	D
γ	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)
β	0.344 (0.005)	0.322 (0.005)	0.319 (0.005)	0.318 (0.002)
Θ	0.545 (0.005)	0.531 (0.005)	0.529 (0.005)	0.529 (0.002)
α	0.078 (0.003)	0.108 (0.005)	0.114 (0.005)	0.114 (0.002)
η	0.008 (0.002)	0.020 (0.004)	0.018 (0.004)	0.019 (0.002)
τ		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.

Table 2

Parameter	A	B	C	D
γ	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)
β	0.344 (0.005)	0.344 (0.005)	0.319 (0.005)	0.319 (0.005)
Θ	0.545 (0.005)	0.545 (0.005)	0.529 (0.005)	0.529 (0.005)
α	0.079 (0.003)	0.079 (0.003)	0.115 (0.005)	0.116 (0.005)
η	0.007 (0.002)	0.007 (0.002)	0.017 (0.004)	0.016 (0.004)
τ			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.

Note: Regressions A-D include year and industry dummy variables which are not shown in order to conserve space. They can be obtained from the authors upon request.

Table 3

Fraction of BEA rates	Estimated γ	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).

¹(Column 1)*(Average BEA depreciation rate = 0.121) + (Column 2).

Table 4

	A	B	C
γ	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)
α	0.166 (0.033)		
η	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.

Table 5
Annual Growth Rate from 1972-96

<u>Type of Equipment Capital Stock</u>	<u>Our Sample</u>	<u>Aggregate Manufacturing</u>
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 γ 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.

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

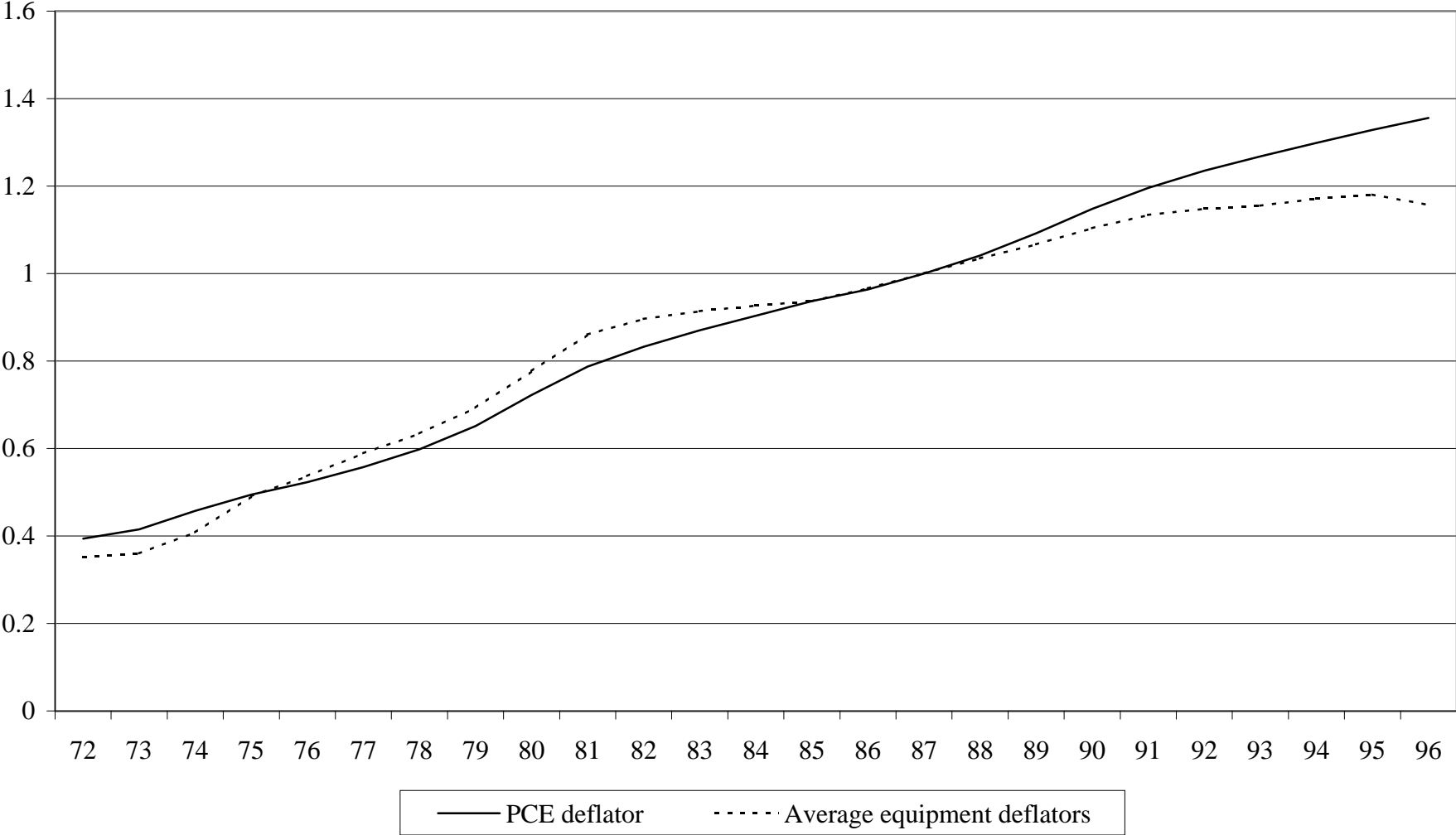


FIGURE 2
Average Depreciation Pattern

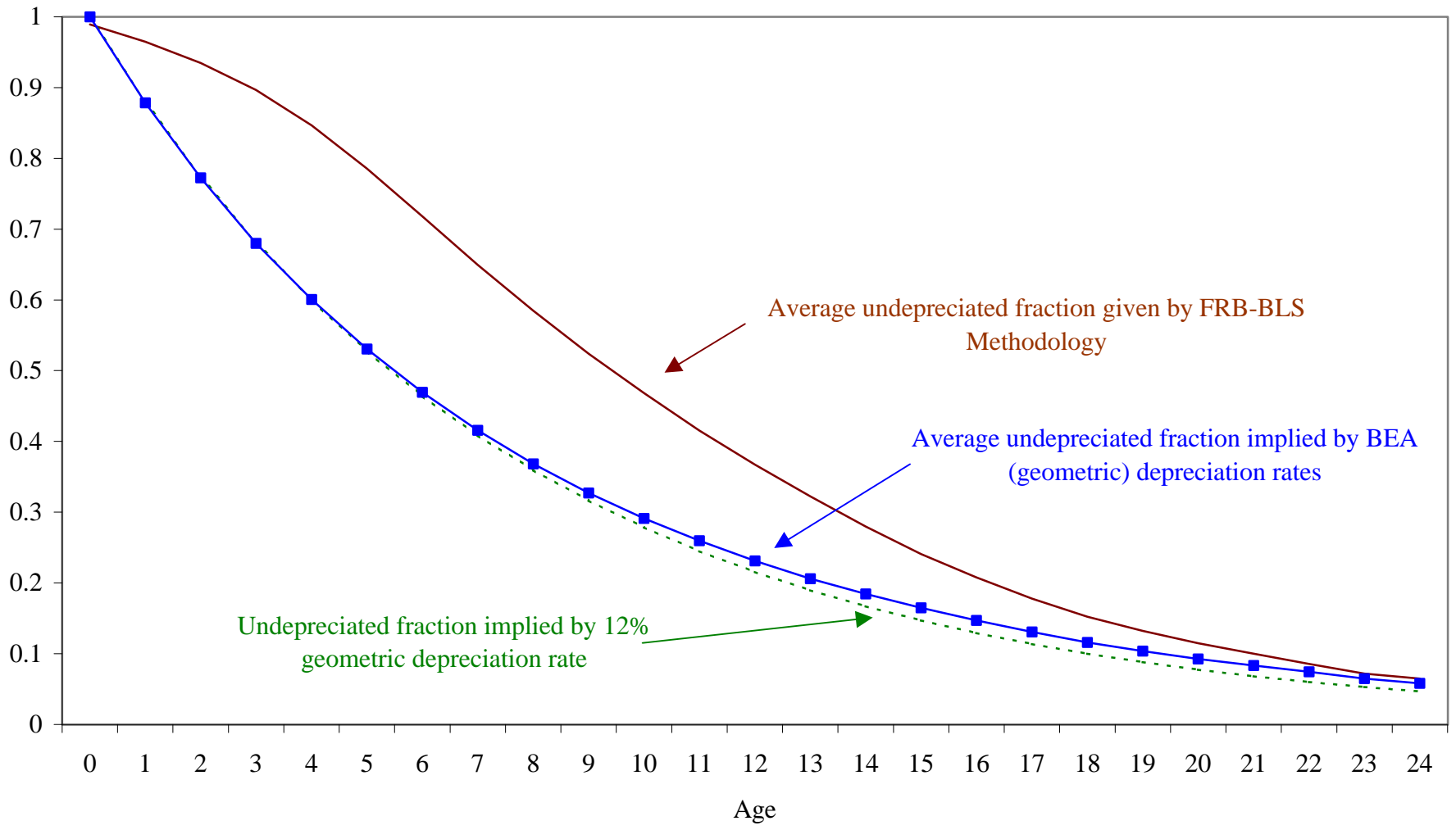
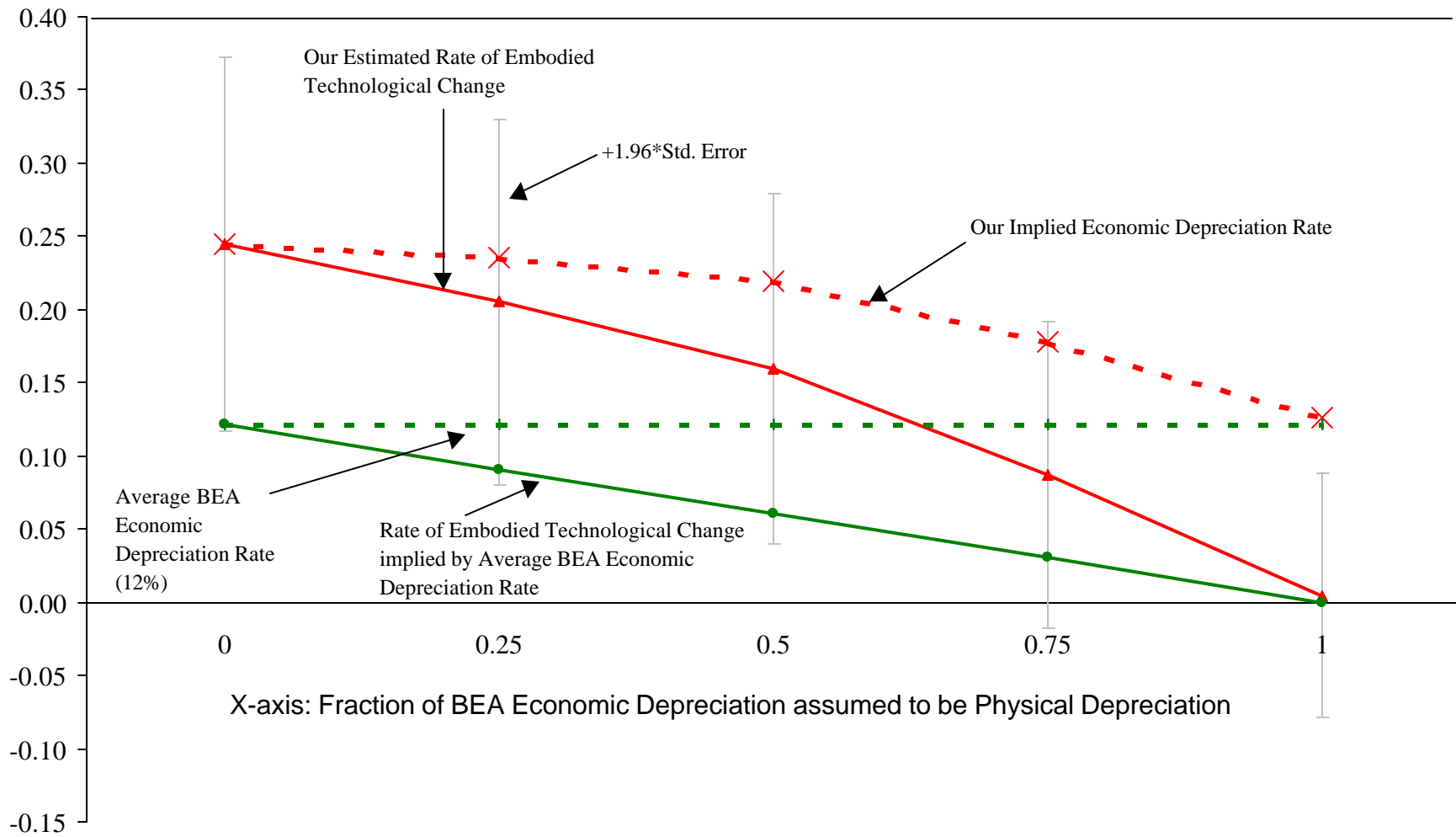


Figure 3



Data Appendix - Variable Construction, Sample Characteristics, and Results from Other Samples

Variable Construction

Each of the data samples described in Section 5 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 Dunne 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:

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

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.

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.

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-A.10 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.¹ 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, 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

¹Over 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.

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.2.² 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 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-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

²The graphs for employment and investment look quite similar.

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}_t , 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.

Regression results using alternative samples

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.”³

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

³ 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.

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.

As mentioned in Section 5 of our paper, our primary sample, POST72A, was chosen so as to minimize the possible effect of several biases. We now present results using other samples.⁴ 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.⁵ 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 survival⁶. 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 γ . 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 1A which displays the results from estimating our full specification using each of our four samples.⁷

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

⁴Section 5 describes the various samples and discusses the potential biases that are involved.

⁵Evidence for this may be found in Baily, Hulten, and Campbell (1992), and Olley & Pakes (1996), among others.

⁶This 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 plants utilize new technologies more intensively than young, small plants.

⁷For 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.

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.⁸ This implies a negative bias on α . Evaluating the likely bias on γ 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 γ .

These priors are in fact supported by the data. The estimate of α 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.

⁸This 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 last large investment.

Table 1A

<u>Parameter</u>	<u>Sample</u>			
	POST72A	POST72B	SCREEN	72-96 PANEL
γ	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)
β	0.319 (0.005)	0.354 (0.004)	0.324 (0.001)	0.299 (0.005)
Θ	0.529 (0.005)	0.496 (0.004)	0.545 (0.003)	0.566 (0.005)
α	0.114 (0.005)	0.112 (0.004)	0.099 (0.002)	0.088 (0.004)
η	0.018 (0.004)	0.019 (0.004)	0.025 (0.001)	0.028 (0.003)
τ	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.

FIGURE A.1
Percentage of All Manufacturing Plants Accounted For By Each Sample

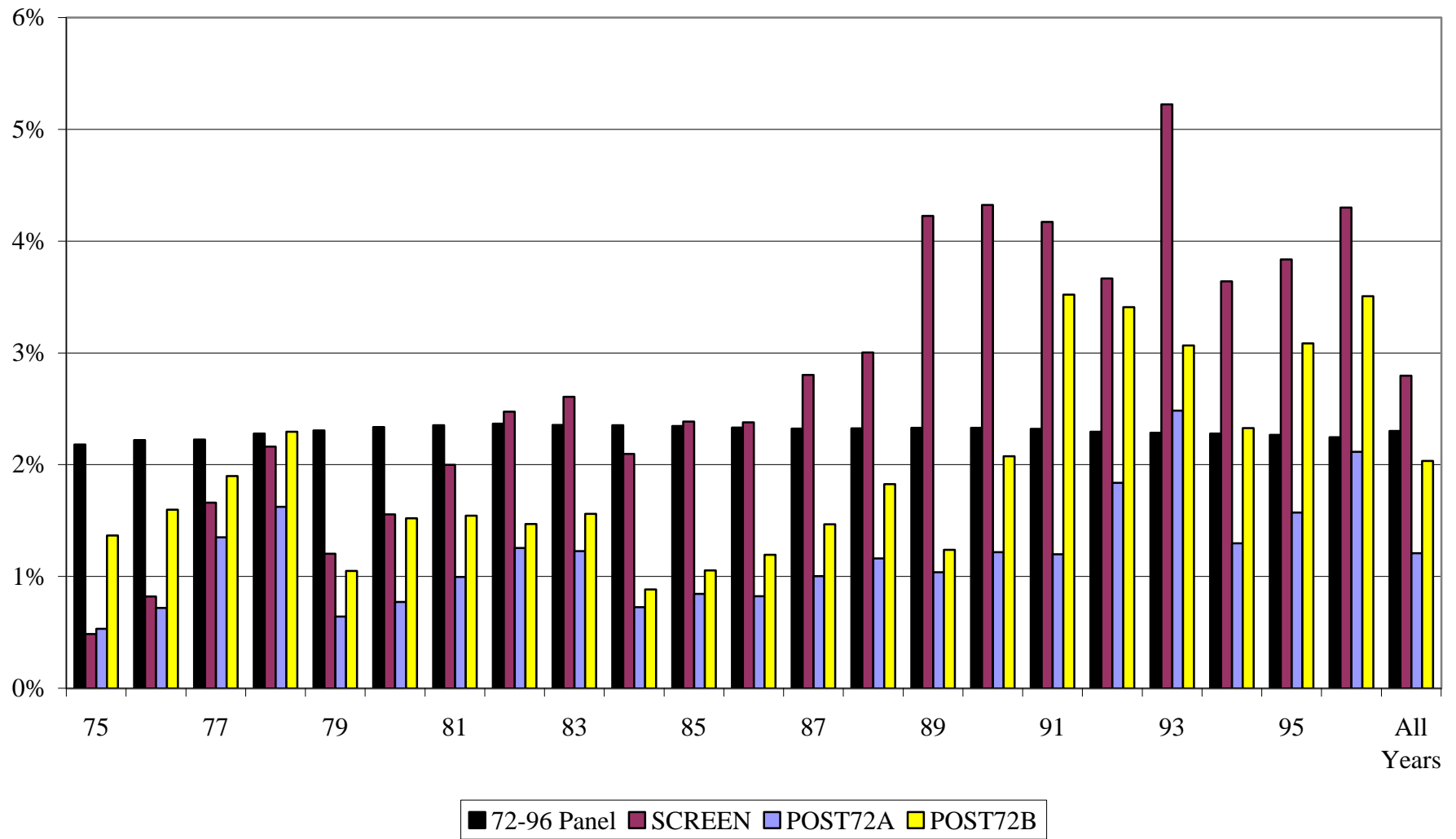


FIGURE A.2
Percentage of Aggregate Manufacturing Shipments Accounted For By Each Sample

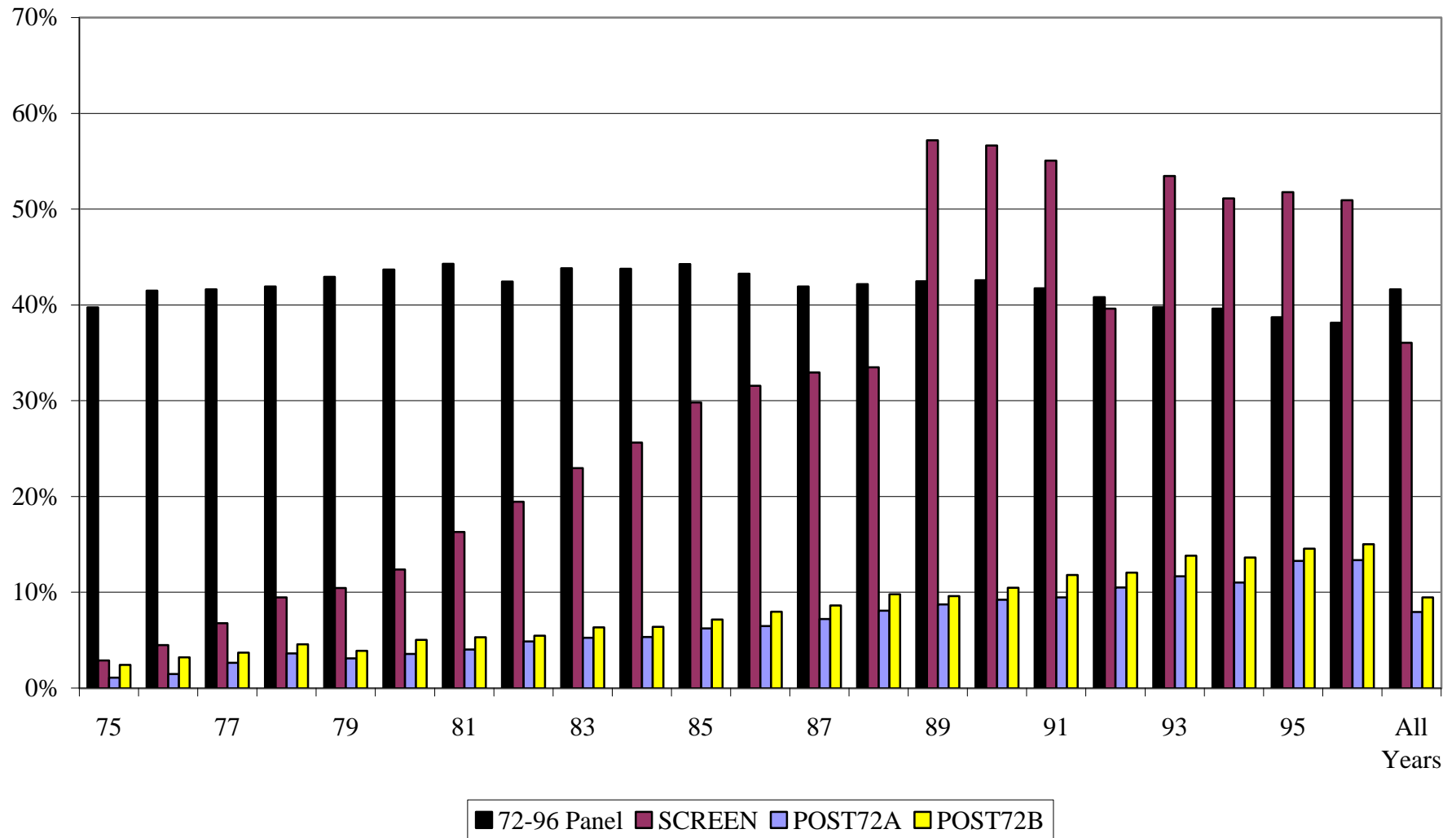


FIGURE A.3
Mean Plant Shipments (in \$1000)

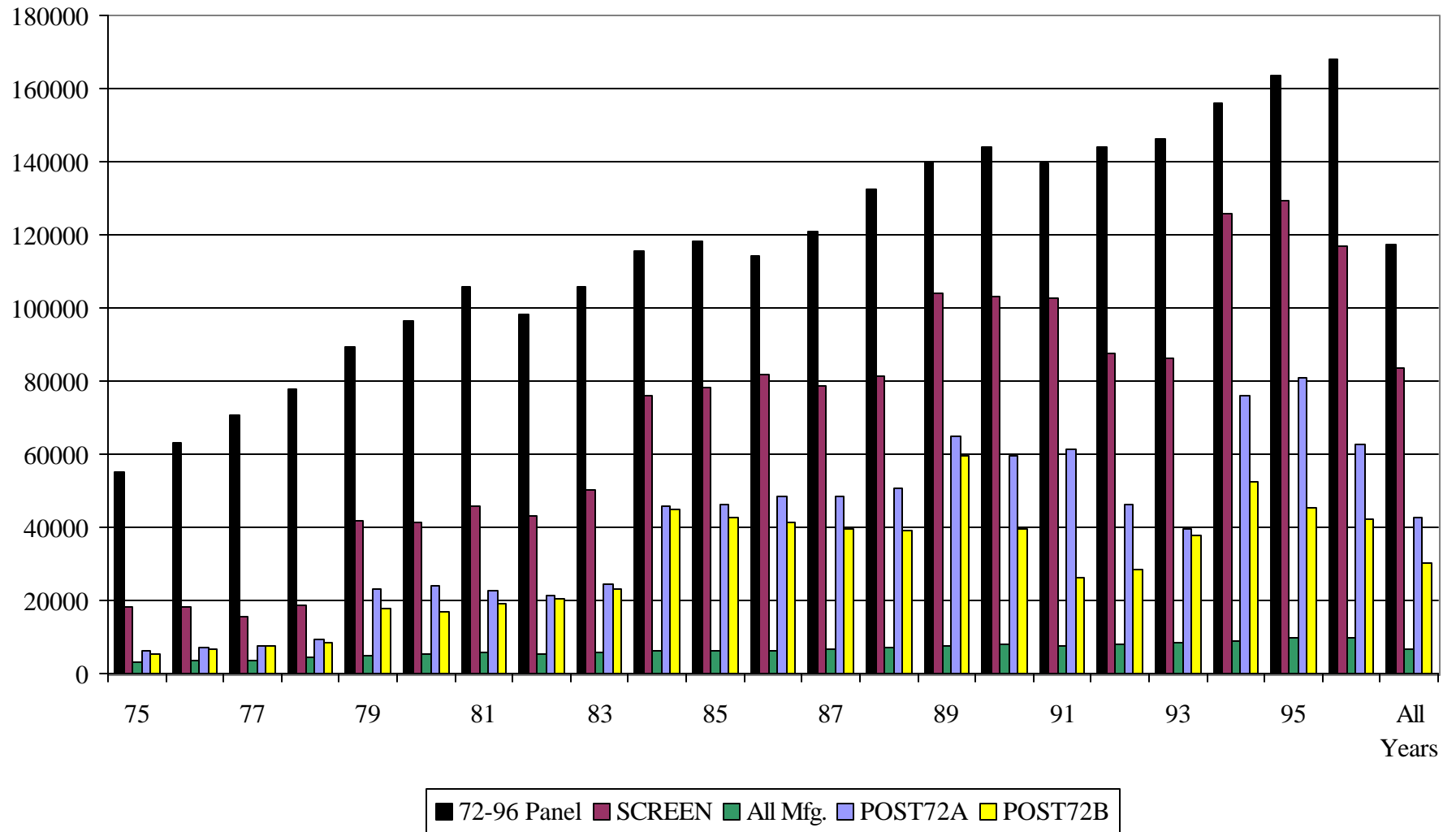
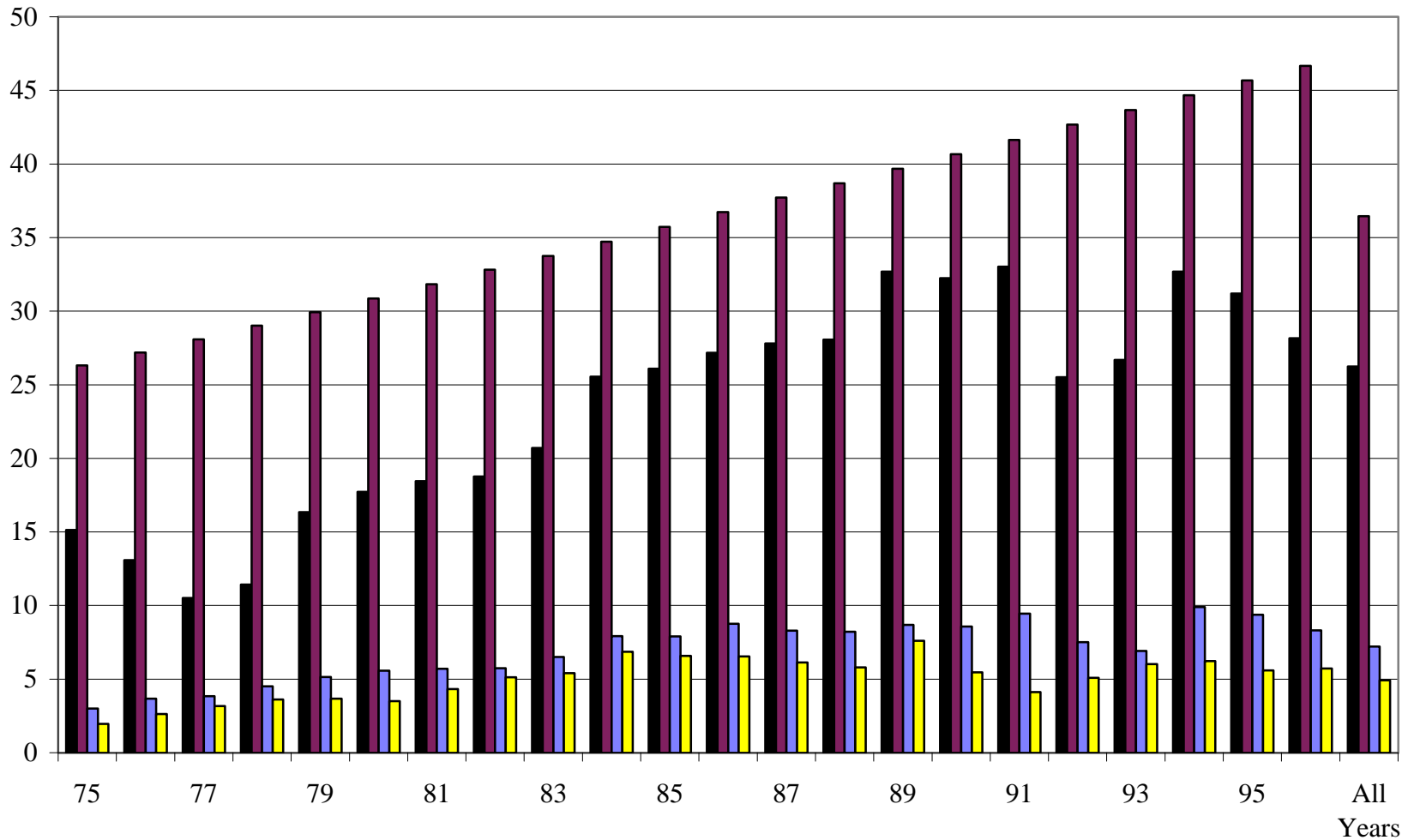


FIGURE A.4
Average Age of Sample Plants By Year



SCREEN
 72-96 Panel
 POST72A
 POST72B

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

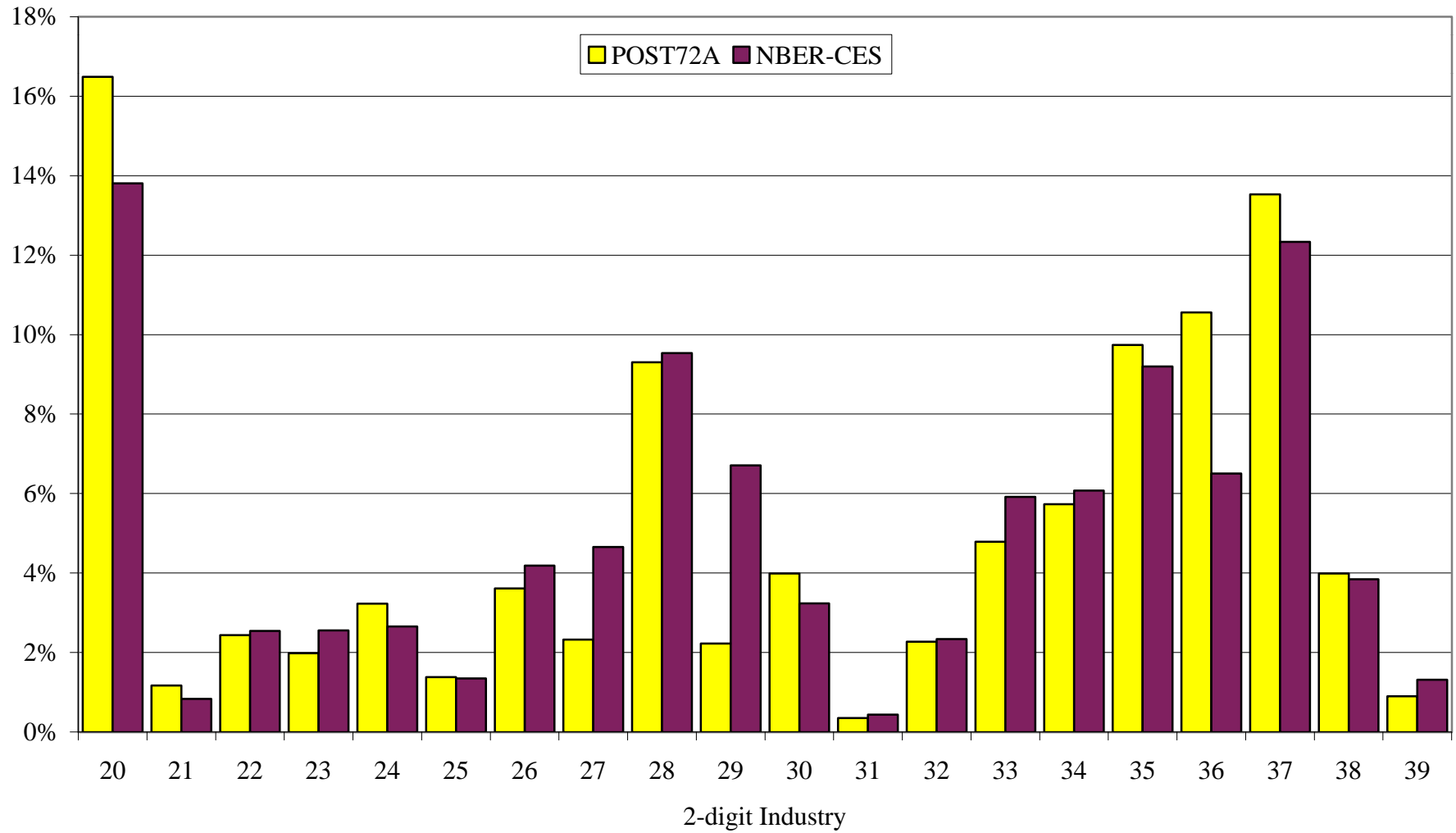


FIGURE A.6
1975-96 Mean 2-digit Industry Shares of Aggregate Mfg. Shipments For POST72B

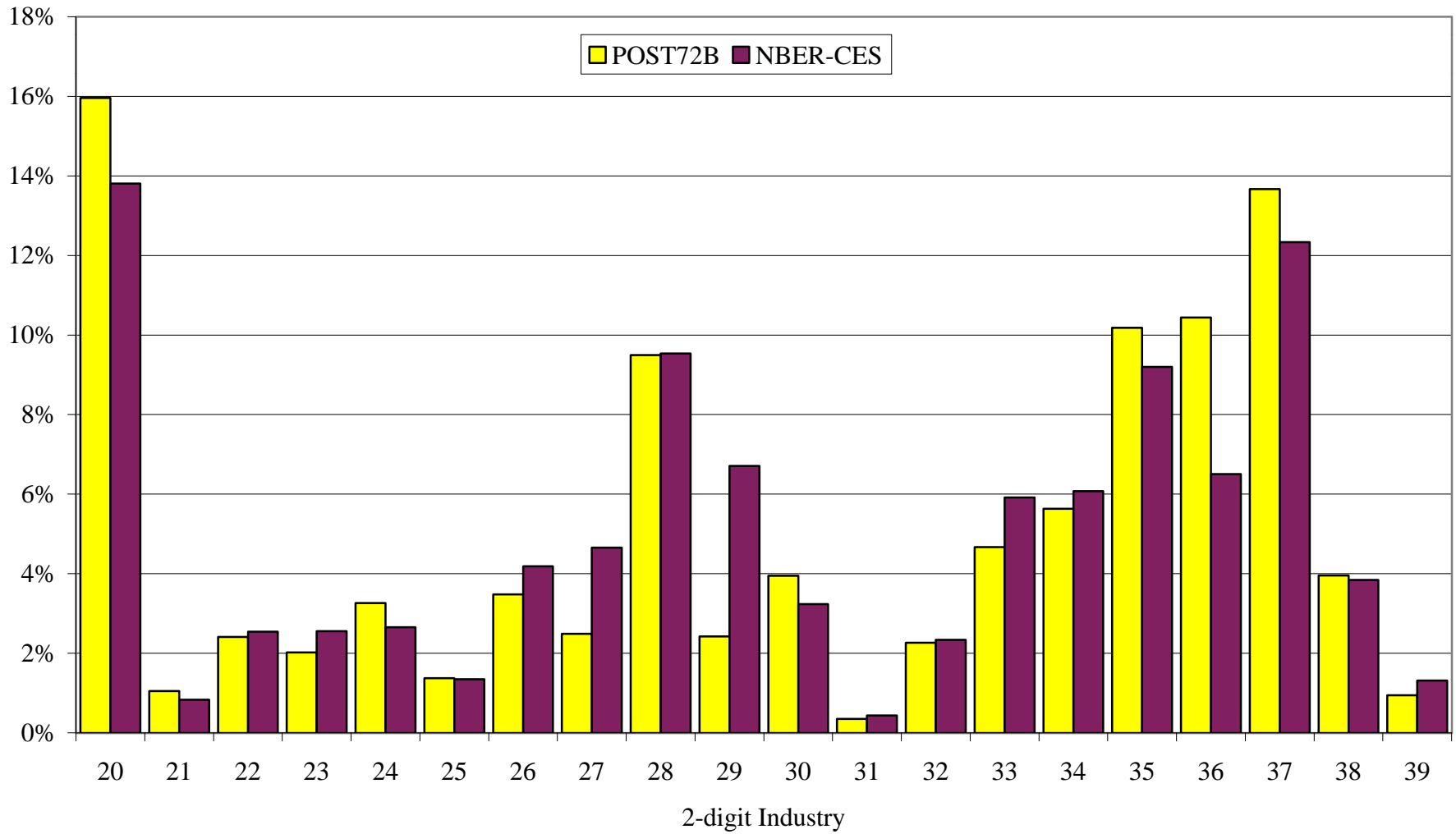


FIGURE A.7
1975-96 Mean 2-digit Industry Shares of Aggregate Mfg. Shipments For 1972-96 Panel

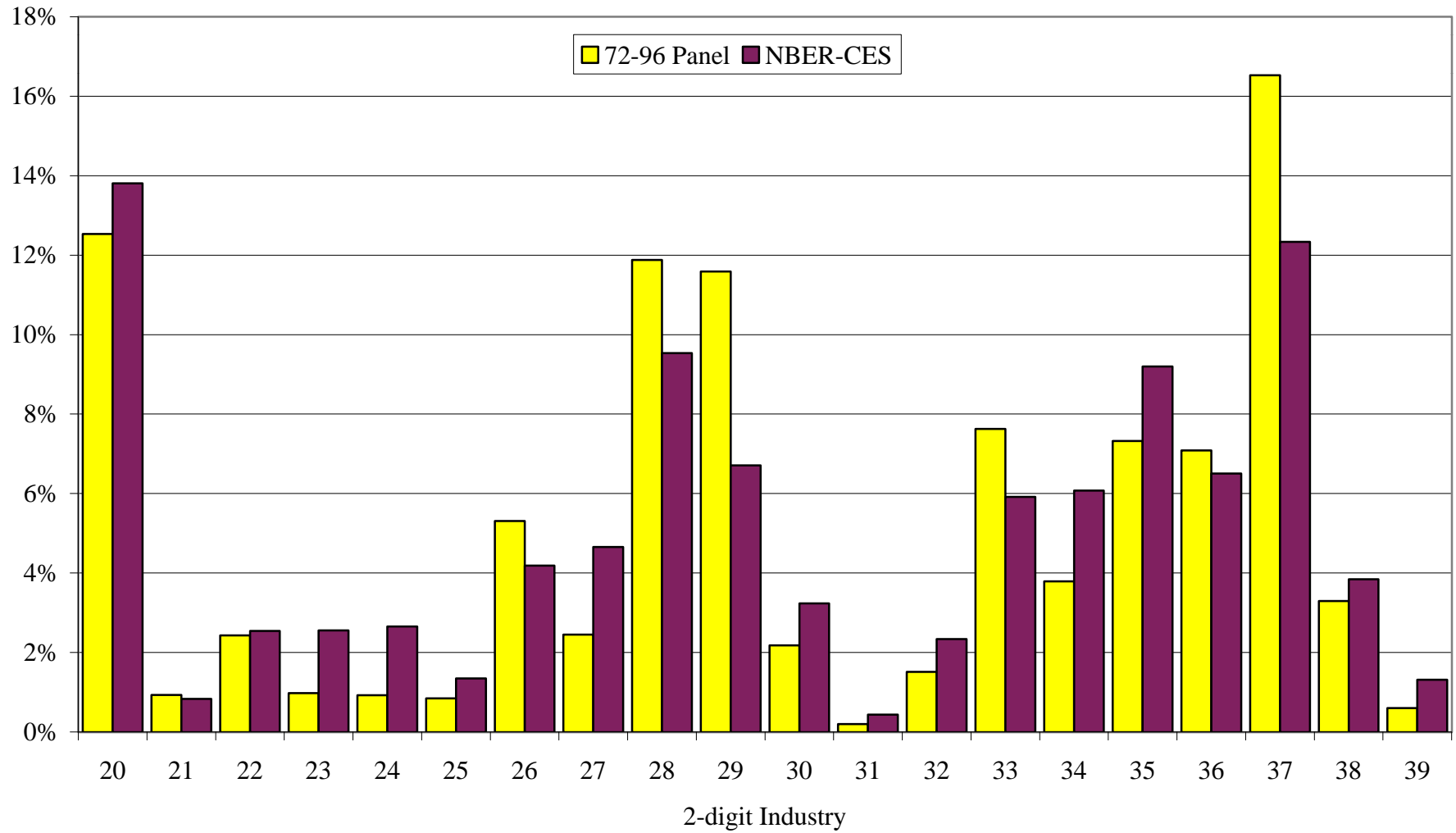


FIGURE A.8
1975-96 Mean 2-digit Industry Shares of Total Mfg. Shipments For SCREEN

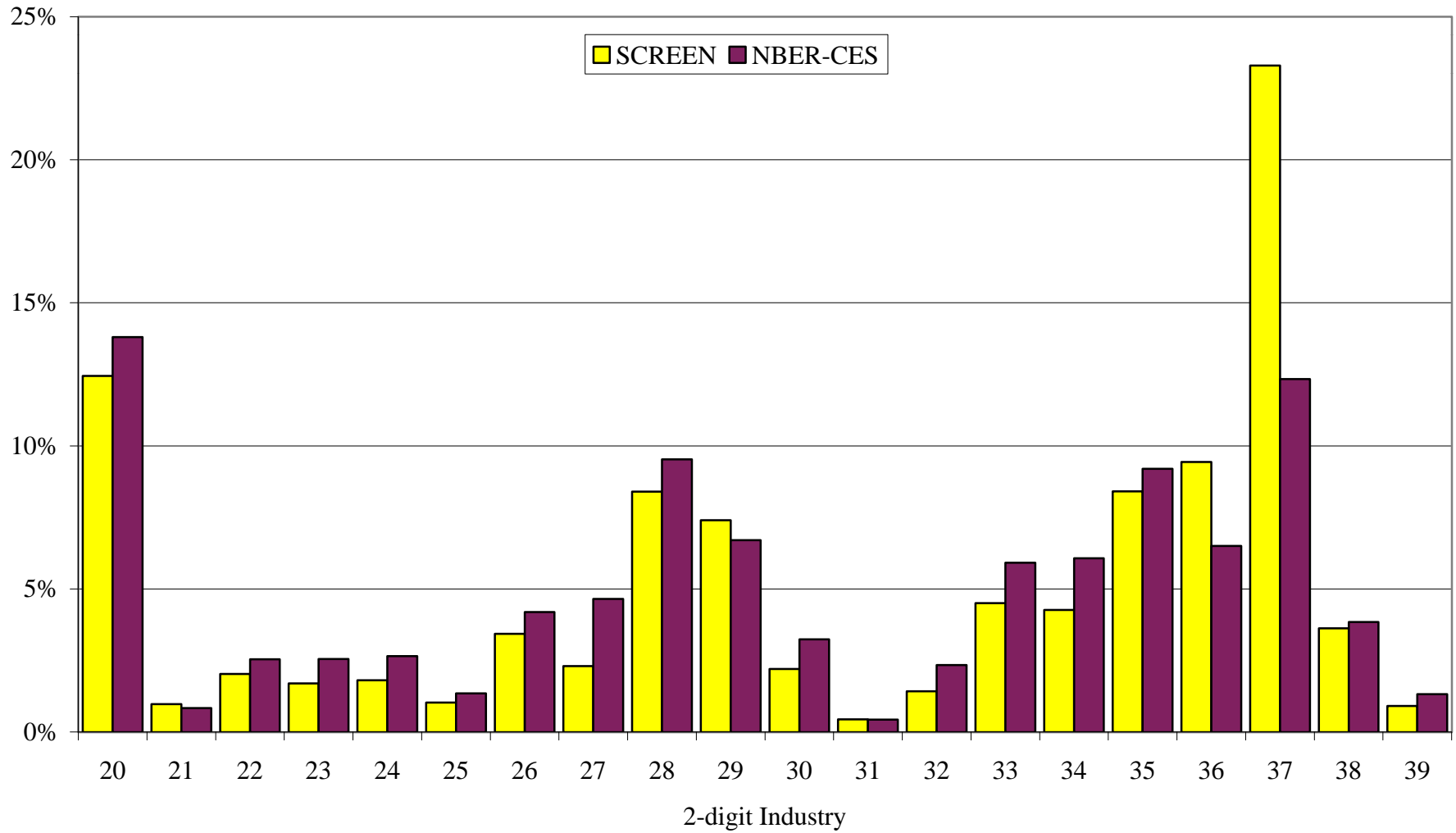


FIGURE A.9
Employment Growth

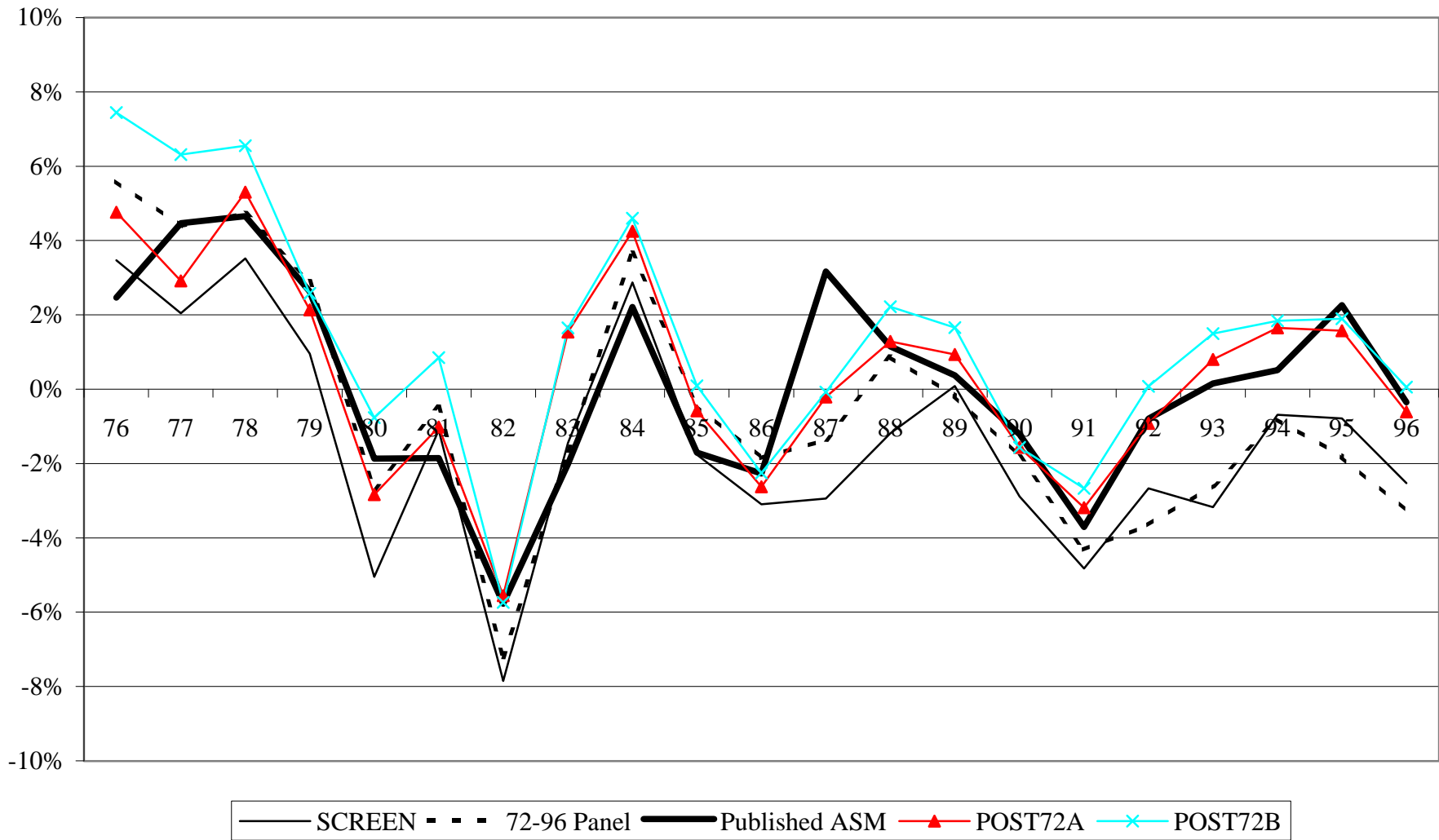


FIGURE A.10
Growth Rates of New (Gross) Investment (Historical \$)

