# IT and Beyond: The Contribution of Heterogeneous Capital to Productivity

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**Abstract**

This paper explores the relationship between capital composition and productivity using a unique and remarkably detailed data set on firm-level investment in the U.S. Using cross-sectional and longitudinal regressions, I find that several capital types, including computers, communications equipment, and software, are associated with current and subsequent years' productivity. The implied marginal products are derived and compared to official data on rental prices; substantial differences exist for a number of key capital types. I also provide evidence of complementaries and substitutabilities among capital goods – a rejection of the common assumption of perfect substitutability. [Keywords: Capital Heterogeneity, Productivity, Investment, Production Function Estimation; JEL Codes D21, D24, D29.]

# 1 Introduction

Does the mix of physical capital that a firm chooses affect its total factor productivity (TFP), and if so, how? In particular, does investment in information and communications technology (ICT) equipment have a greater impact on productivity than investment in other capital goods? Is the contribution of certain capital goods greater (or less) when they are used together rather than separately? These questions are of fundamental importance to understanding the nature of the production function. They are also particularly relevant for understanding the sources of the rapid rise in aggregate productivity over the last decade, a period in which ICT investment has grown tremendously. Using the micro-level data from a unique, highly detailed survey of U.S. businesses (the 1998 Annual Capital Expenditures Survey), I address these and other important questions related to heterogeneous capital investment and productivity.

Although there has been a great deal of research in recent years regarding the relationship between information technology (IT) capital (and, to a lesser extent, ICT capital) and productivity, there has been little if any research that has gone beyond IT to consider effects from the entire capital mix.[1] The special focus on IT is understandable given its increasingly ubiquitous application in business and personal life. However, there are several reasons to expand our attention beyond the productivity impact of IT to the impact of other capital goods as well, and, in fact, to expand our attention to the impact of the capital mix more generally. First, computers and communications equipment are not purchased in isolation. They are often purchased in conjunction with other capital goods to build a system of capital to accomplish productivity enhancements. Wilson (2004), in fact, using the full 1998 ACES sample of nearly 30,000 firms, provides evidence of exactly that.[2] Thus, even if our interest is only in the productivity impact of IT, we must account for its correlation with other capital goods that have their own impact on productivity.

Second, given that in practice firms typically have budget constraints on total capital expenditures, policy prescriptions calling for increased investment in IT are

[1]An important exception is Caselli and Wilson (2004), which used country-level data on capital imports to explore the determinants of capital composition and its effects on income per capita.

[2]Specifically, Wilson (2004) finds that the share of Computers in total firm investment is positively correlated with the investment shares of Other Office Equipment, Software, Furniture, Office Buildings, Commercial Buildings, and several other types of capital.

of little practical value without prescriptions as to what type(s) of capital should be replaced. For this purpose, one must know the productivity impacts of every type of capital. Third, nearly all micro-level production studies assume a single, homogenous capital stock (two at most). In reality, capital is clearly heterogeneous. In fact, even the standard Neoclassical model, which assumes perfect substitutability among capital goods, calls for capital heterogeneity to be taken into account.[3] If one goes even further by allowing imperfect substitutability, then one confers unto the capital mix an even greater role in determining productivity.

The goal of this paper is to begin to fill in this gap in the literature. Part of the cause of this gap has been a lack of micro data on investment across a wide range of capital goods. The recent Annual Capital Expenditures Survey (ACES) of 1998, however, goes a long way towards addressing this need. The 1998 ACES, conducted by the U.S. Census Bureau, is a unique data set containing investment by 55 separate types of capital for a representative sample of roughly 30,000 businesses spanning the U.S. private nonfarm economy. The ACES does not, however, collect information on other factor inputs such as labor. By matching the publicly-traded ACES companies to the Compustat research file, I am able to observe not only these firms' quantities of factor inputs in 1998, but also the quantities of factor inputs and output in other years as well. Thus, I can explore the cross-sectional and, to some extent, longitudinal relationship between capital mix and productivity.

Most previous micro production studies, especially those focusing on IT capital, have been restricted to the manufacturing sector.[4] Thus, not only does this paper move the literature forward in terms of the focus on heterogeneous capital, it also moves it forward by offering results based on a much broader coverage of the economy (as well

[3]In the standard (Jorgensonian) Neoclassical model, different capital goods are assumed to have different marginal products (and user costs) which depend on depreciation rates, tax considerations, and price appreciation, as shown in the seminal work Hall and Jorgenson (1967). The capital service flow from an individual capital good is the product of its capital stock and its user cost. Total capital services is then a function (e.g., a sum) of the individual capital services. (See Jorgenson and Stiroh (2000)). Unfortunately, micro-level data typically do not provide information on individual capital stocks and thus micro-level production studies typically omit capital mix which, even under this Neoclassical model, should affect both output and conventionally-measured TFP.

[4]Notable exceptions are Doms, Jarmin, and Klimek's (2002) study of retail trade, Hubbard's (2004) study of the trucking industry, and Greenan and Mairesse's (2000) analysis of French services (in addition to manufacturing).

as offering results separately for manufacturing and nonmanufacturing).[5] It should also be noted that this paper covers a time period, 1998-2001, far more recent than most other contemporaneous studies.[6]

I first estimate the effect of each capital type's share of investment on conventionally-measured TFP in the current and subsequent years. TFP here is a productivity residual, obtained in three alternative ways (all based on a standard Cobb-Douglas production function): (1) a production function regression, (2) a labor productivity regression, and (3) an index of multi-factor productivity constructed using factor shares. Exploiting the fact that I have data for years prior to the 1998 investment decision as well as after, I assess the extent to which firm fixed, or slow-moving, effects such as workplace practices may be responsible for any links between productivity and particular types of investment. Third, in order to address the issue of complementarities and substitutabilities among capital goods, I estimate the effects of combining different pairs of capital types together on productivity.

The results indicate that several capital types, including but not limited to computers, communications equipment, and software, are associated with current and subsequent years' productivity. These results are robust to including either future TFP or a polynomial of investment, capital, and age (a la Olley and Pakes (1996)) in the regressions – both techniques for directly controlling for unobserved "transmitted" productivity components. On the other hand, I find evidence suggesting that these capital types are correlated with other slow-moving, intangible capital. By using official (BLS) data on depreciation rates, I show that one can back out the implied marginal products for each capital type from these regression coefficients. These marginal products can then be compared to the rental prices by capital type provided by the BLS. For the most part, the implied marginal products are strikingly similar to these rental price estimates. However, for a few key types like computers, communications equipment, and software, the implied marginal product is found to be substantially higher than the official rental price.

I also find evidence that certain "bundles" (i.e., pairs) of investments have an added effect on productivity. In fact, using any reasonable division of types into "high-

[5] As pointed out by Brynjolfsson and Hitt (1996): "A convincing assessment of [Information Spending] productivity would ideally employ a sample which included a large share of the economy..., but at a level of detail that disaggregated inputs and outputs for individual firms...."

[6] For example, Gilchrist, et al. (2003) explore the 1986-93 period; Brynjolfsson and Hitt (2003) covers 1987-94; Black & Lynch (2001) covers 1987-93; and Lehr & Lichtenberg (1999) covers 1977-93.

tech" and "low-tech" categories, the data shows that high-tech capital goods tend to be complementary with low-tech capital goods and substitutable with other high-tech capital; likewise low-tech capital goods are substitutable with other low-tech capital. Not only does this result have interesting implications for productivity, it also is a rejection of the conditions required for the existence of a single capital aggregate, a common assumption in most production functions.

One important aspect of the ACES investment data should be emphasized here. The 1998 ACES provides data on *investment* by asset type, but not *capital stock* by asset type (and there are no prior years of disaggregate data with which to build stocks). One would prefer, of course, to have the latter given that theory suggests a relationship between *capital* composition and productivity, not *investment* composition (beyond its contribution to capital composition) and productivity. However, as discussed in Section 3, given data on depreciation rates, one can still properly obtain the marginal products implied by the investment share coefficients as long as firms are, on average, approximately near steady-state.

# 2 Background

As mentioned at the start of the paper, up to this point the literature on the productivity impact of disaggregate investment has focused almost exclusively on computers and communications equipment (and mostly just computers). The macroeconomic literature has typically relied on growth accounting exercises to explore the issue, while microeconomic studies have generally relied on firm- or establishment-level production function estimation, with IT capital as a separate production input in addition to labor and non-IT capital.[7]

During the 1980s and the first half of the 1990s, most studies found little or no evidence of an economically important contribution of ICT to productivity or productivity growth. Examples include Oliner and Sichel (1994), Griliches and Siegel (1992), and Berndt and Morrison (1995). Berndt and Morrison (1995), in fact, find that ICT capital's share of total capital services is negatively related to multi-factor productivity

[7] On the macro side, see Oliner and Sichel (1994, 2000), Jorgenson and Stiroh (2000), and Gordon (2000). On the micro side, see Brynjolfsson and Hitt (1996, 2003); Lehr and Lichtenberg (1999); Greenan and Mairesse (2000); and Gilchrist, Gurbuxani, and Town (2003). For similar analyses at the industry-level, see Berndt and Morrison (1995); Gera, Gu, and Lee (1999); and Stiroh (2002).

(MFP) in panel fixed-effects regressions using data on 2-digit manufacturing industries from 1968-1986.

More recently, a consensus appears to be forming that IT investment is associated with higher productivity, although the magnitude, direction of causality, and timing of this impact is still very much under debate.[8] Oliner and Sichel (2000) used growth accounting techniques to identify the contribution, within a standard Neoclassical production framework, of ICT capital to aggregate productivity growth. They find that the use and production of ICT equipment together account for two-thirds of the acceleration in productivity growth that occurred between the first half and the second half of the 1990s.

Greenan and Mairesse (2000) find evidence that computer use has a positive impact on productivity at the firm level using data on the French manufacturing and services sectors. However, they cannot reject the hypothesis that computer's contribution to productivity is the same as the contribution of other capital. Gilchrist, Gurbaxani, and Town (2003) use a modified version of the Arellano and Bond (1991) GMM estimator to estimate the elasticity of the IT capital stock via both a production function and a total factor productivity (TFP) framework. They find that IT's elasticity in the production function is about equal to its cost share and is not significant in the TFP regression (both consistent with normal returns within the Neoclassical model). However, they also find that personal computers (PCs) have an impact on productivity above and beyond their contribution to the IT stock. They find this is driven by the durable goods sector; PCs have no impact in the nondurables sector. Brynjolfsson and Hitt (2003) estimate the elasticity of computers using both short- and long-difference regressions. They find that computers' elasticity is consistent with their cost share in the short differences; but, consistent with Gilchrist, *et al.*, the long difference results suggest that the elasticity is significantly higher than computers' cost share.

As discussed in Section 1, the productivity literature up to this point has generally focused exclusively on computers (and, to a lesser extent, communications equipment) in so far as it has explored disaggregate investment at all. The investment

[8] The issues of this debate are discussed in Stiroh (2003), which performs a meta-analysis of the literature on estimating the elasticity of output with respect to IT capital. He shows that estimates of this elasticity are sensitive to the time period and industry coverage of the data, the model specification, and the econometric technique.

literature, however, has explored the implications of capital heterogeneity for adjustment costs (e.g., Chirinko (1993)) and tax policy (Goolsbee (2004); Cummins, Hassett, and Hubbard (1994)). Most relevant to this paper, Cummins and Dey (1998) estimate a structural model in which heterogeneous capital goods are allowed to differentially affect the production and adjustment technologies and find important effects of imperfect substitutability. Their capital stock data, however, is only broken down into two groups: equipment and structures.

# 3 Model

The focus of this paper is on the relationship between capital mix and productivity at the firm level. In the typical Neoclassical production framework, once the service flow of total capital is accounted for, capital mix plays no role in determining output. Consider the standard Cobb-Douglas (ex-post) production function in capital and labor with a Hicks-neutral technology shift parameter (subscripts for time and firm are omitted to economize on notation): $Y = AK^{\alpha}L^{\beta}$. Assuming the necessary and sufficient conditions for the existence of a single aggregate $K$ hold (see Solow (1955-1956) and Fisher (1965)), $K$ can be considered the sum of disaggregate (real) capital stocks – stocks differentiated either by type or by vintage (here by type).[9] The production function can then be written as follows:

[9] Solow (1955) established that a necessary and sufficient condition for the existence of a single capital aggregate, $K = g(K_1, K_2)$, is that the marginal rate of substitution between different capital types is independent of the quantity of labor (i.e., the heterogeneous capital types must be weakly separable). In addition, Fisher (1965) demonstrated that if different types (or vintages) of capital embody different levels of quality/technology, then there is an additional necessary and sufficient condition for the existence of a single capital aggregate: the heterogeneous quality must be expressible in homogenous constant-quality units – this is the well-known "better = more" assumption. Taken together, these two conditions are equivalent to requiring that different capital types be perfect substitutes once they are properly expressed in constant-quality units. For the majority of the paper (until Section 7), I assume these conditions hold although I do not make the further assumption that ex-post marginal products per dollar of investment are equal across capital subaggregates.

$$
\begin{aligned}
Y &= A\sum_{p=0}^{N}\left[(1+\theta_p)\,K_p\right]^{\alpha}L^{\beta}\ ;\ \theta_0=0 \\
&= A\left[1+\sum_{p=1}^{N}\left(\theta_p\xi_p\right)\right]^{\alpha}K^{\alpha}L^{\beta}
\end{aligned} \tag{1}
$$

where $K = \sum_{p=0}^{N} K_p$ and $\xi_p = K_p/K$; $p$ indexes capital types: $p = 0, 1, ..., N-1$, where $N$ is the number of types. Each $K_p$ is measured in physical units, or equivalently, by the current dollar value of capital. The weights, $(1+\theta_p)$, convert the dollar value of capital of type $p$ to quality units that can be compared across types; the quality of $K_0$ is used as the numeraire. $K$ is the total dollar value of capital.

Capital type $p$'s relative marginal product is:

$$
\frac{\partial Y}{\partial K_p}/\frac{\partial Y}{\partial K_0} \equiv F_p/F_0 = 1+\theta_p. \tag{2}
$$

Thus, $\theta_p$ represents the percentage difference between capital type $p$'s marginal product and the marginal product of the numeraire capital type. In the standard Neoclassical model, optimizing firms choose the quantity of each input such that its marginal product is equal to its price. (In this case, the input is said to be earning normal returns). The ratio between the marginal products of different capital stocks is therefore equal to the ratio of their user costs (see Jorgenson (1963)). Thus, the Neoclassical model would predict that $1+\theta_p = (c_p/c_0)$, where $c_p$ and $c_0$ are the user costs for type-$p$ and type-0 capital, respectively. However, there are a number of possible reasons for $1+\theta_p \neq (c_p/c_0)$. First, there could be adjustment costs and/or learning-by-doing processes that differentially affect capital goods. Second, there may be unobserved organizational co-investments associated with particular capital goods. Third, due to uncertainty regarding the rate of return on capital investments, there could be systematic expectational errors by firms that may be more severe for certain capital goods.

Notice that in the above framework, different capital types are perfectly substitutable (once their quality has been accounted for by $\theta_p$). In section 7, I relax this assumption by allowing capital goods to be complementary or substitutable with other capital goods. In other words, I allow the marginal product of capital type $p$ to depend on the quantity of each and every other capital type.

The principal focus of the following section is on obtaining consistent estimates of the sequence of $\theta_p$s ($\{\theta_p\}_{p=1}^{P}$), i.e., the coefficients on the investment shares. To estimate the $\theta_p$s via linear regression, the production function must first be linearized. If $\sum_{p=1} \theta_p \xi_p \approx 0$, then, to an approximation, the production function in logs (lowercase letters denote logs) becomes[10]:

$$y = a + \alpha \left[\theta_1 \xi_1 + ... + \theta_P \xi_P\right] + \alpha k + \beta \ell \tag{3}$$

At least three regression specifications allowing for the estimation of $\{\theta_p\}$ can be derived from (3).[11] First, adding an i.i.d. disturbance term, equation (3) forms a regression equation from which one can estimate the parameters $a$, $\alpha$, $\beta$, and $\{\theta_p\}$. Second, the production function specification can be converted into a labor productivity specification by subtracting $\ell$ from both sides of (3).[12] Third, assuming constant returns to scale and perfect competition, we can measure $\alpha$ and $\beta$ using capital and labor's income shares ($\tilde{\alpha}$ and $\tilde{\beta}$), respectively, and subtract ($\tilde{\alpha}k + \tilde{\beta}\ell$) from both sides of (3) in order to obtain a measure of (log) multi-factor productivity (here, 2-factor productivity, (2FP)):

$$2fp = y - (\tilde{\alpha}k + \tilde{\beta}\ell), \tag{4}$$

$$\text{where } \tilde{\beta} = wL/pY \text{ and } \tilde{\alpha} = rK/pY = 1 - \tilde{\beta}.$$

[10] Any approximation error introduced here is likely to result in a negative bias in OLS estimation of the $\theta_p$s. For simplicity, consider the case where there is only one capital type ($p = 1$) in addition to the numeraire type. As $\theta_1 \xi_1$ diverges from zero, the approximation error, $\log(1 + \theta_1 \xi_1) - \theta_1 \xi_1$, which is an omitted variable in the estimation, will become increasingly negative. So if the true $\theta_1$ is nonzero, then the omitted variable will be more negative for firms with larger shares of investment in type 1 ($\xi_1$). Hence, there will be a negative bias on the estimator of $\theta_1$. In particular, notice that any findings of excess returns that we obtain are likely to be underestimates whereas findings of below-normal returns may be overstated.

[11] A similar formulation, containing disaggregate capital shares in addition to total capital, was employed in the empirical studies of Berndt and Morrison (1995) and Lehr and Lichtenberg (1999), though to a much more limited extent. The former disaggregated capital into office equipment, other equipment, and structures; the latter broke capital into IT and non-IT capital.

[12] In the labor productivity regressions for which I report results below, I assume constant returns to scale so that labor can be excluded as a regressor.

Here $w$, $r$, and $p$ are the prices of labor, capital, and output, respectively. The 2fp specification is then:

$$2fp = a + \alpha \left[\theta_1 \xi_1 + ... + \theta_P \xi_P\right] + \epsilon \tag{5}$$

where $\epsilon$ is an i.i.d. disturbance term.

Notice that in each of these specifications, the regression coefficient on $\xi_p$ actually represents $\alpha\theta_p$, not $\theta_p$. One must divide the estimated coefficient on $\xi_p$ by an estimate of the total capital elasticity in order to back out $\theta_p$.

As noted in the introduction, an important limitation of the 1998 ACES data is that it only contains disaggregate investment, not disaggregate capital stocks. Hence, capital shares (the $\xi_p$s) are unobserved. Investment shares, however, are not; and with the proper data, capital shares can be approximated from investment shares. From the standard perpetual inventory equations, $I_{pt}^i = \triangle K_{pt}^i + \delta_p K_{p,t-1}^i$ and $I_t^i = \triangle K_t^i + \delta K_{t-1}^i$, one gets:

$$\frac{K_{p,t-1}^i}{K_{t-1}^i} = \frac{(g_t^i + \delta)}{\left(g_{pt}^i + \delta_p\right)} \cdot \frac{I_{pt}^i}{I_t^i}$$

where $g_{pt}^i = \triangle K_{pt}^i / K_{p,t-1}^i$ and $g_t^i = \triangle K_t^i / K_{t-1}^i$ are the growth rates of capital type $p$ and total capital, respectively. Unfortunately, $g_{pt}^i$ is unobserved in our data. If $g_t^i$ and $g_{pt}^i$ are small (relative to the depreciation rates), as would be expected in a steady state, the first term in the product above is approximately equal to the ratio of total depreciation to type-$p$ depreciation.[13] Above, I showed that $\theta_p$ represents the relative marginal product of type-$p$ capital (minus one). Using investment shares in lieu of capital shares in our regressions thus changes the interpretation of $\theta_p$ from $[(F_p/F_0) - 1]$ (eq. (2))to $[(F_p/F_0) - 1]\,(\delta/\delta_p)$. Likewise, I showed above that the Neoclassical prior (based on firms setting factor quantities until marginal products equal factor prices) for this parameter is $(c_p/c_0) - 1$. Using investment shares, this prior becomes $[(c_p/c_0) - 1]\,(\delta/\delta_p)$. In section 5.3, I back out the marginal products implied by the estimated $\theta_p$s and compare them to the widely-used user cost estimates generated by the Bureau of Labor Statistics (BLS).

Returning to the specifications discussed above, the shift variable $a = \log(A)$ is an unobserved variable that is likely to vary by firm and may possibly be correlated

[13] Lehr and Lichtenberg (1999), in their study of the returns to computer capital, similarly approximated capital shares using the product of investment shares and this ratio of depreciation rates.

with the other regressors. To formalize this possibility let us rewrite $a$ as:

$$a_{it} = f_i + \omega_{it} + v_{it}. \tag{6}$$

The first term, $f_i$, is a firm fixed effect. The second term, $\omega_{it}$, is a productivity shock that is known ("transmitted") to the firm when it makes its input decisions but is unobserved to the econometrician. The third term is the productivity innovation that is *ex-ante* unknown even to the firm. It is this third term that we are after: the relationship between the capital mix and $v_{it}$ represents the causal effect that capital mix has on productivity. The concern regarding the regressions described above is that both $f_i$ and $\omega_{it}$ may be correlated with firm's investment decisions, including the capital composition decision, leading the OLS estimators of our parameters to be biased.

As for the fixed effect, $f_i$, often one can control for it through panel data methods (e.g., first-differencing). In this paper, however, I have only a single cross-section of data (1998) on $\{\xi_p\}$, though I do have panel data for the variables $y$, $k$, and $\ell$ (below I discuss an alternative exercise which makes use of this panel data, though not to identify $\{\theta_p\}$). Due to this limitation of the data, the primary identification strategy is to focus on the cross-sectional estimation and include as many potential correlates with unobserved contributors to productivity (i.e., with $f_i$ and $\omega_{it}$) as possible.

First, I include a number of variables measuring permanent firm characteristics. These consist of 3-digit SIC level industry dummy variables, state dummies, and a 5-category indicator of firm size (employment); this size variable is described in Appendix A. The state (of headquarters) dummy is included because a number of studies have found that location has an important effect on firm performance; this effect can be due, for example, to networks/technological spillovers or density (see Audretsch & Feldman (1996), Ellison & Glaeser (1997, 1999), Audretch & Dohse (2004), Hall & Ciccone (1996)). Second, we include a dummy variable indicating whether or not the firm had an investment spike (defined as investment 20% or more of the beginning-of-year book value of capital).

As discussed in Section 6, I also experiment with two more direct approaches to controlling for the unobserved, transmitted productivity component. The first is the Olley and Pakes (1996) approach of proxying for the shock with a polynomial function of (total) investment, capital, and age. The second approach is to include a measure of one-year-ahead MFP (specifically, $2fp_{t+1}$) as an additional regressor. Both of these approaches are discussed in more detail in Section 6. In both cases, the estimated coefficients on the investment shares are virtually unchanged relative to the baseline results.

One issue that must be addressed before proceeding is the appropriate measure of output ($Y$). Typically, one assumes that real value added is produced using capital and labor, as in $Y = AK^{\alpha}L^{\beta}$. However, properly measuring real value added can be quite difficult, especially at the micro level. The most common measure is double-deflated value added, which is deflated gross output ($\approx$sales) minus deflated materials. Separate deflators for materials costs are generally unavailable. Moreover, even if they were, double-deflated value added has been shown to be a biased measure of real value added in the presence of imperfect competition (see Basu & Fernald (1996)).

In light of these problems with value added as a measure of output, I opt instead to use gross output. Since gross output is a function of materials, as well as capital and labor, one must decide on how materials enter into the production function. One option is to have materials as an additional factor in the Cobb-Douglas production function:

$$Y = AK^{\alpha}L^{\beta}M^{\gamma}. \tag{7}$$

In practice, though, materials tend to dominate the explanatory power of capital and labor in micro-level estimation, making it difficult to identify the coefficients on capital and labor. Another option is to assume that value added ($AK^{\alpha}L^{\beta}$) and materials have a Leontief relationship and therefore materials can be excluded from the gross output production function (this is an approach often followed in the micro production estimation literature[14]). I follow the latter approach for the most part in this paper. As a robustness check, however, I also report results based on a regression specification derived from equation (7) (see Section 5.4 below).

[14] See, e.g., Bahk and Gort (1993).

# 4 Data

## 4.1 The Regression Sample

The principal sources of data for this paper are the 1998 Annual Capital Expenditures Survey (ACES) and Compustat.[15] The ACES is conducted annually by the U.S. Census Bureau to elicit information on capital expenditures by U.S. private, nonfarm companies. This information is used by the BEA in constructing the National Income and Product Accounts (NIPA).[16]

In typical years, the ACES queries companies on their expenditures on total equipment and total structures, in addition to related values such as book value of capital assets, accumulated depreciation, retirements, etc.. In the 1998 survey, however, the ACES additionally required firms to report their investment broken down by 55 separate types of capital – 26 types of equipment and 29 types of structures. A list of these types is given in Table 1. The 1998 ACES is unique as the only large-scale micro-level U.S. survey of investment that disaggregates investment into a full range of detailed asset types (i.e., beyond simply total equipment and total structures, and beyond just one or two asset types such as computers or transportation equipment). These data on disaggregate investment allow us to observe the complete composition of firms' investment, which is the focus of this paper.

The 1998 ACES sampling frame consists of all U.S. private, nonfarm employers.[17] All companies with 500 or more employees were surveyed while smaller employers were surveyed based on a stratified random sampling such that larger firms were sampled with a higher probability. Response to the ACES is legally required so response rates are extremely high. In the end, responses were obtained from nearly 34,000 firms, with around 28,000 reporting some positive investment.

Unfortunately, aside from sales, book value of total capital assets, and invest-

[15] For more details regarding the 1998 Annual Capital Expenditures Survey, including the published aggregate data and the actual survey questionaires, see Census Bureau (2000).

[16] The ACES is the primary source of data used by the BEA to construct estimates of aggregate investment for non-manufacturing industries. As described below, the 1998 ACES collected data on investment by detailed asset type; this information is now being used by the BEA in constructing its Capital Flows Tables and its Fixed Reproducible Tangible Wealth estimates, but only in a very limited way. See Becker, Haltiwanger, Jarmin, Klimek, and Wilson (2004) for more on this issue.

[17] In addition, a sample of companies with zero employees were sent an abbreviated questionaire which did not request the disaggregate investment detail.

ment, the ACES does not collect information on other key variables needed for productivity analysis. Most importantly, ACES does not record employment levels. To obtain data on these other variables, I match the ACES data to the Compustat research file.[18] The drawback of this merger is that Compustat only covers publicly-traded companies, which are a small subset of the firms in ACES (as in the overall economy), albeit a subset of very large firms that account for a large share of U.S. economic activity. Matching ACES to Compustat in 1998 yields a sample of roughly 3,000 firms (though about half of these firms had missing values for at least one of the variables needed for the productivity regressions below). An advantage of merging with Compustat, though, in addition to its provision of key productivity-related variables, is that it provides an annual time-series of data. The majority of firms in the 1998 matched sample were also present in Compustat in 1999-2001, allowing us to observe the relationship between investment composition and productivity in future years as well as the current year. Most of the matching firms are also included in Compustat in 1995-1997, which allows us to test for reverse causality to some extent.

## 4.2 Investment Patterns and Summary Statistics

Before getting into the analysis of the relationship between the composition of capital (across types) and productivity residuals, it is useful to consider the relevant patterns that have been found regarding disaggregate investment behavior at the micro-level as well as the basic characteristics of our sample. Wilson (2004) uses the full 1998 ACES sample, with around 28,000 firms, to establish a number of interesting stylized facts about firms' investment behavior in terms of heterogeneous capital. Two of those findings are of particular relevance here.

First, he finds that investment (at least reported investment) tends to be concentrated in a small number of capital types, though what exactly these types are varies from firm to firm. This is particularly true for structures capital: 72% of the firms that reported having some structures investment did so in only a single structure type (only 11% had investment in more than two types)[19]; yet no single structure type av-

[18] A bridge file linking Compustat's unique firm identifier, CUSIP, with the unique firm identifier in the ACES was generously provided (and constructed) by Ron Jarmin and Kristen McCue of the Center for Economic Studies, U.S. Census Bureau.

[19] 39% of the firms in ACES had at least some structures investment; 78% had some equipment investment.

erages more than 20% of total structures for these firms. Equipment investment tends to be more diverse across types. For instance, 55% of equipment-buying firms had investment in three or more types of equipment. For both equipment and structures, investment diversity tends to increase with firm size. In particular, among firms at or above the 90th percentile of sales – a group which roughly corresponds to the Compustat sample – over 70% invested in three or more types of equipment, 25% invested in three or more types of structures. These statistics imply that for many types of capital, especially structure types, investment is a rather uncommon phenomenon. Thus, the contribution of these capital types to productivity may be exceedingly difficult to identify. For this reason, I decided to condense the 55 ACES type categories down to 20 types in order to reduce the frequency of zeros in the investment shares, and hence increase their cross-sectional variability.[20] The mapping from the original 55 ACES categories to the 20 categories used in this paper is shown in Table 1.

The second finding from Wilson (2004) of particular relevance here is that capital goods vary greatly in terms of how widely used they are among industries. Of the 55 capital types shown in Table 1, Computers are the most widely used, followed by Software.[21] For instance, using the sample weights in the ACES to get an appropriate economy-wide estimate, the top four investing industries accounted for only 24% of computer investment in 1998. For Software, this "top-4 industry concentration ratio" was just 26%.[22] This seems to confirm the common perception of these capital types as "general purpose technologies." Other widely purchased capital goods were Other Office Equipment and Manufacturing, Processing, and Assembly Plants. Conversely, many other capital goods, especially structure types, are extremely concentrated in just a few industries (with top-4 industry concentration ratios above 90%).

These findings affect the interpretation of the coefficients on the type-specific investment shares in our regressions. The regressions contain 3-digit SIC industry dummies, but if a capital good tends to be highly concentrated, what we may be identifying with its share coefficient is actually an industry effect below the 3-digit level.

[20] In addition, as a robustness check on the main regression results reported below, I tried excluding firms which reported investment in fewer than 3 capital types (at the 20-type level). This had virtually no effect on the regression results, as this restriction excluded very few firms from our sample.

[21] Throughout the paper, capital type names are capitalized to indicate that they refer to specific categories of capital listed in Table 1.

[22] Somewhat surprisingly, Communications Equipment turned out to be rather concentrated, with an industry concentration ratio of 87%.

In the description below of the regression results, the focus is generally on the "general purpose" capital goods such as Computers, Software, Instruments, Fabricated Metal Products, etc.. Other asset categories, particularly structures, are predominately industry-specific asset types. Their inclusion in these regressions serves more to control for industry effects not accounted for by the 3-digit SIC industry dummies.

Now, let us turn briefly to the basic characteristics of our regression sample. Table 2 provides summary statistics for the main variables used in the analysis below. One can see here that the firms in this sample are indeed quite large. Sales among these firms averaged roughly $2.4 trillion in 1998 and they employed an average of 12,559 workers. These firms collectively accounted about 25% of gross output and 17% of employment in the U.S. private nonfarm economy.[23]

The average number of different equipment types that these businesses bought was 4.6. Not surprisingly, the average number of structure types was much lower, at 1.7. On average, they spent 15% of their total capital expenditures on Computers, 16% on Special Industry Machinery, 11% on Miscellaneous Equipment, and less than 10% on each other capital type. The lowest average investment share is 1% (for Trucks). It is interesting to note that firms in the sample reported much less investment, on average, on Software and Communications Equipment, each with about 3% of total investment, than on Computers.[24]

It is also worth noting the raw correlations between sales and each of the variables in our regressions. These are shown in the last column of Table 2. Interestingly,

[23] The sales figures here are based on the Compustat Net Sales variable (#A12). Total sales for the sample was $3.473 trillion and total employment was 18.348 million. According to the BEA's gross output by industry data, private nonfarm gross output in 1998 was $13.961 trillion. Total private nonfarm employment in 1998 was 106.021 million (from BLS *Earnings and Employment*).

[24] This contrasts with National Income and Product Accounts (NIPA) data which shows Software investment in 1998 was actually slightly greater than Computer investment. The difference likely comes from how ACES and NIPA treat expensed software. In the ACES, firms are instructed to report investment in software "only if capitalized as part of a tangible asset" and to exclude it "if the purchase is considered intangible (e.g., licensing agreement) or if expensed such as office supplies." The NIPAs, on the other hand, classify all software expenditures as investment regardless of whether the firm accounts for the expenditures as capital or intermediate expenses. (Note that software that is bundled with, or embedded in, hardware is not counted as software investment in either ACES or NIPAs.) The 2003 ACES, which like the 1998 survey will request investment by detailed asset type, will also include a supplemental survey requesting the amounts expensed on Computers, Communications Equipment, Software, and instruments.

Computers have virtually no correlation with sales and Software is actually negatively correlated with sales, even though, as shown below, these capital types are positively associated with sales in a multivariate production function regression analysis.

# 5 Results of cross-sectional regressions

## 5.1 Production Function Regressions

Tables 3-5 present the main results of the cross-sectional regressions (described above in Section 3. Table 3 presents the estimates of the parameters in equation 3. In parentheses, robust (Huber-White) standard errors are shown. The first column of results pertains to a regression containing only 1998 variables. Results in the second column are from a regression where all variables, except the investment shares (which are only available in 1998), are 1999 values. The third and fourth columns refer to regressions for 2000 and 2001, respectively. Again, the dependent variable here is log gross output; the independent variables are log labor (number of employees), log capital stock (deflated book value), all investment shares except one (Special Industry Machinery)[25], and dummy variables controlling for 3-digit industry, state of the firm's headquarters, the employment size class of the firm, and whether the firm engaged in an investment spike in 1998. The coefficients on the industry and state dummies are not disclosed in order to avoid confidentiality concerns.

We include the investment spike dummy because firms with an investment spike may incur high adjustment costs in 1998 and subsequent years which will be reflected in lower output and productivity than they otherwise would obtain. Conversely, the spike may reflect the firm's response to a positive productivity shock (as in Olley and Pakes (1996)). Either way, it should be included in our regressions since investment spikes may consist disproportionately of certain capital goods, thus excluding the spike

[25] One investment share must be omitted to avoid linear dependence of the investment shares. This is consistent with the model in Section 3, as there we defined $\theta_p$ relative to some numeraire type, $\theta_0$. Special Industry Machinery was chosen as the omitted category based on the *a priori* expectation that it has a lower marginal product than most other capital goods. Though the level of the coefficient on each investment share depends on the choice of omitted category, this choice does not affect the coefficient relative to other types' coefficients. Moreover, when I compare the estimated coefficients to user cost measures from the BLS, the BLS measures are also expressed relative to Special Industry Machinery.

variable could bias the coefficients on the investment shares of those capital goods.

The results show that Computers, communications equipment, and software are statistically significantly associated, usually above the 99% level, with higher productivity (i.e., output controlling for capital and labor) for all four years in our sample, 1998-2001. The computer coefficient is generally around 0.5, suggesting that an increase in the computer investment share by 10 percentage points (relative to the omitted capital type) would be expected to be associated with 5% higher output, which, since we're controlling for capital and labor, implies 5% higher multi-factor productivity. The computer-productivity link appears to be slightly higher in 1998 and 1999 than in 2000 and 2001 (though the differences are not statistically significant).

At their peak, software and communications equipment have even larger effects. Software's coefficient is 0.93 is 1998 and declines thereafter to 0.63-0.65 in 2000 and 2001. Communications Equipment's coefficient is around that of computer's, 0.5, in 1998, but then rises to 0.7-0.8 in subsequent years. A closer look at how these coefficients vary over time is presented in Section 6.

Some other types of capital also have significant coefficients. Offices are positively and significantly (at above the 99% level) associated with productivity for all four years in our sample. Aircraft have a negative and significant coefficient in 2000. Lastly, General Purpose Machinery has a positive and significant coefficient in 2001.

I estimate the elasticity of output with respect to labor to be .49-.53 and the elasticity of output with respect to capital to be .41-.44. These estimates are reasonable, though the estimates of labor's elasticity are somewhat below that implied by factor shares while capital's elasticity estimates are somewhat above.

The coefficient on the spike variable is positive and significant for 1998 and 1999. Its value implies that a spike is associated with 7-8% higher output in the current and following year. The effect becomes smaller and insignificant in subsequent years. Firm size, as proxied by employment size, has no significant relationship with productivity in these regression, all else equal (which is not surprising given that $\log(L)$ is already included in the regression).

## 5.2 Labor productivity and 2FP regressions

Overall, the results from the labor productivity regressions, shown in Table 4, are nearly identical to those from the production function regressions discussed above. As in the production function regressions, Computers, Communications Equipment, and

Software are statistically significantly associated, usually at the 99% level, with higher productivity for all four years in our sample, 1998-2001. The coefficient values and the time path of coefficients on these types is also similar to those in Table 3. Also as in the production function regressions, Offices are positively and significantly (at above the 99% level) associated with labor productivity for all four years in our sample, while Aircraft investment is negative and significant in 2000 and General Purpose Machinery is positive and significant in 2001.

The coefficient on the capital-labor ratio implies an elasticity of output with respect to capital of .40 to .45, which is reasonable though perhaps slightly higher than expectations. The spike variable is found to have the same effect in the labor productivity regression as the production function regression: a spike is associated with 7-8% higher labor productivity in the current and following year, with the coefficient becoming smaller and insignificant in subsequent years.

As discussed in Section 3, one can also estimate the set of parameters $\{\theta_p\}$ using a multi-factor productivity specification. When we use 2FP as the dependent variable and regress it on the investment shares, the precision of the estimates of the investment share coefficients is reduced (relative to the production function or labor productivity specifications). This is likely because the measure of 2FP, which relies on observed factor shares, contains a good deal of noise – stemming mostly from the fact that labor expenses had to be imputed for the majority of firms due to frequent nonreporting of labor expenses in Compustat. Nonetheless, the results with 2FP as the dependent variable are broadly consistent with those from the production function or labor productivity regressions.

The results of the 2FP regressions are shown in Table 5. Again, evidence is found of a positive and significant relationship between investment and multi-factor productivity for Computers, Communications Equipment, Software, and Offices. These relationships are found in all four years, with the exception of Communications Equipment in 1998 and Computers in 2001 (in both cases, the estimated coefficient has a p-value just over 10%).

## 5.3 Interpretation of Results

In section 3, I showed that the coefficient on a particular investment share represents $\alpha\theta_p = \alpha\left[(F_p/F_0) - 1\right](\delta/\delta_p)$, i.e., the (ex-post) marginal product of the capital type (relative to the omitted type), adjusted for its relative depreciation rate, times the elasticity of capital in the production function. Under the Neoclassical assumption that firms equilibrate marginal products to factor prices, this coefficient should thus equal $\alpha\left[(c_p/c_0)-1\right](\delta/\delta_p)$, where $\alpha$ is the elasticity of capital; $c_p$ and $c_0$ are the user costs for type-$p$ and type-0 capital, respectively; and $\delta$ and $\delta_p$ are the depreciation rates for total capital and type-$p$ capital, respectively. The U.S. Bureau of Labor Statistics (BLS) provides estimates of depreciation rates, as well as estimates of user costs, at a detailed capital type level (which has a many-to-one mapping to our 20-type level). The data are widely used by researchers and other government agencies in the construction of capital stock data. Using our estimate of $\alpha$, along with the BLS measures of $\delta$ and $\delta_p$, one can thus back out the implied ratio of marginal products between capital type $p$ and the numeraire capital type. Further, taking the BLS estimate of the user cost of the numeraire type – in our case, Special Industry Machinery – as approximately equal to the marginal product of this capital type, one can back out the marginal product (per dollar of capital) for every capital type.

Using the coefficient estimates from the baseline regression results for 1998, the implied marginal products by type of capital are shown in Table 6. Column (1) shows the implied marginal products based on the production function regression results shown in column (1) of Table 3. Columns (2) and (3) show implied marginal products based on the labor productivity and 2FP regressions, respectively. The fourth column provides the user cost estimates for 1998 provided by the BLS.[26] The asterisks next to each implied marginal product indicate the degree to which it is statistically significantly different from the BLS estimated user cost. The confidence intervals here assume that everything in the expression $\alpha\left[(c_p/c_0)-1\right](\delta/\delta_p)$ is known with certainty except the variable of interest, $c_p$.

For most capital types, the implied marginal product is strikingly similar to the BLS user cost. This is especially true if one uses the production function or labor productivity estimates. For a several capital types, however, the implied marginal product is found to be significantly (statistically and economically) higher than the BLS estimate of the user cost. In particular, using the production function estimates, Computers are found to have had an ex-post marginal product of 61% in 1998, compared to the BLS's estimated user cost of 41%. Communications Equipment had an estimated marginal product of 27%, compared to a 16% estimated user cost (though

[26]The BLS actually estimates user costs (rental prices) by asset type *and* industry. To arrive at a single user cost estimate for each asset type, I simply average across all industries.

this difference is significant at just the 10% level). Software had an estimated marginal product almost three times higher than the BLS's user cost, 137% vs. 48%. This says that one must pay \$1.37 in order to rent \$1 worth of software for a year. One must pay more than \$1 because its value depreciates so quickly that in order to get an entire year's worth of service flow from software, one must pay a high rental rate. To put it differently, to provide oneself with \$1 worth of service flow for a year, one would need to buy \$1 worth of software more than once during the year.

The estimated marginal products for Commercial Buildings, Industrial Buildings, Offices, Utility Structures, and Other Structures are also statistically significantly higher than their BLS user costs. However, this result should be viewed with caution. First, though statistically significant, the differences for these types are fairly minor (ranging from 4-9 percentage points). Second, as noted earlier, structures capital tends to be infrequent and heavily concentrated among industries. Therefore, the estimated coefficients on their investment shares may, to some extent, reflect industry effects not picked up by the 3-digit industry dummies included in the regressions.

As mentioned in Section 3, there are a number of possible reasons why the estimated ex-post marginal product for a capital good could be different than its user cost. First, there could be adjustment costs, including learning costs, that disproportionately affect particular capital goods. Second, certain capital goods may be associated with unobserved organizational co-investments. For example, a number of authors have argued that organization co-investments, such as human resource management (HRM) programs, training programs, quality control systems, etc., contribute to productivity and are facilitated by ICT capital.[27] Third, due to uncertainty regarding the rate of return on capital investments, there could be systematic expectational errors by firms that may be more severe for certain capital goods. For instance, it is often posited that firms systematically overinvested in Communications Equipment in the late 1990s. Interestingly, though, I find that in fact the marginal product on Communications Equipment during this period was actually above its user cost.

## 5.4 Robustness Checks

In the regression specifications thus far, intermediate inputs (materials, $M$) were not included in the gross output production function as we maintained that value added

[27]See, e.g., Bartel, Ichniowski, and Shaw (2004a); Black and Lynch (2001); Bresnahan, Brynjolfsson, and Hitt (2001).

and materials are weakly separable. I now relax that assumption as a robustness check. Assuming that gross output is a Cobb-Douglas function of $K$, $L$, and $M$, one can derive two additional specifications. The first specification is identical to the production function specification above (equation (3)) except that it includes log materials as an additional regressor. The point estimates and significance of the investment share coefficient are not qualitatively affected by this change (and therefore are not shown).

As another robustness check related to materials, I estimate the 2FP specification using double-deflated value added instead of gross output in the construction of 2FP. The drawbacks of this approach are (1) that we lack separate deflators for gross output and materials to use in the double deflation, and (2) the double-deflated value added measure may be biased under imperfect competition (Basu & Fernald (1996)). Using this alternative measure of 2FP yields similar results to those obtained using the gross output version of 2FP, though the estimates are somewhat less precise.

Another alternative way to measure 2FP in this paper is to use the reported sales data collected in ACES rather than the sales data collected in Compustat. Obviously, since the ACES data cover only 1998, we can only construct this ACES version of 2FP (gross output) for 1998. If we use the ACES version of 2FP in our 1998 regression (full specification), again Computers are found to have a positive and highly significant (above 99% level) relationship with 2FP. This regression also yields positive and significant coefficients on Communication Equipment and Cars & Light Trucks.

In sum, our various alternative regressions are virtually unanimous in finding a positive and statistically significant relationship between Computer's share of investment and productivity. This is true for productivity in the current year and at least the subsequent three years, though the effect appears to be strongest for productivity one year out. Communications Equipment and Software are also found to have a significant positive relationship with productivity in the majority of our regressions. Other capital types are occasionally found to be significantly related to productivity, but for none, except Office Buildings, is the relationship particularly robust. As mentioned earlier, since investment in structures is heavily determined by industry, the association between structures types, such as Office Buildings, and productivity may be reflecting industry effects not fully captured by the 3-digit industry dummies.

### 5.5 Manufacturing vs. Nonmanufacturing

It is conceivable that certain capital goods would have different ex-post rates of return in manufacturing than in nonmanufacturing. Since the same capital good may be used for different purposes in manufacturing than in nonmanufacturing, there could be differences between the two sectors in the degree of adjustment costs, the organizational co-investments, and errors in expectations as to the return from investment in the capital good. Therefore, an interesting extension of the regressions discussed above is to allow the coefficients to vary between manufacturing and nonmanufacturing. To implement this extension, I create a manufacturing dummy variable and then include interactions between it and each of the regressors in the baseline production function regression above (Table 3). I also include the dummy variable by itself so as to allow the intercept to vary by sector. The results are shown in Table 7.[28] Columns (1), (3), (5), and (7) show the estimated coefficients (and standard errors) for the overall sample, while Columns (2), (4), (6), and (8) shows the estimated coefficients on the manufacturing interactions.

As before, I find that, on average, Computers, Communications Equipment, Software, and Office Buildings are generally found to be positively and significantly related to productivity over the entire sample (though not necessarily for all of these types in all four years). In addition, Commercial Buildings is found to have a negative relationship with productivity in 2000 and 2001. Oddly, Instruments has a significantly positively coefficient in 2000 but a significantly negative coefficient in 2001.

As for the manufacturing interactions, the investment shares for Instruments, Commercial Buildings, Utility Structures, and Other Structures have significantly higher estimated returns in the manufacturing sector (in at least 3 of the 4 years). The higher return on Instruments in manufacturing may be because the kinds of instruments used in manufacturing are actually different than those used in nonmanufacturing (e.g., scientific/measuring instruments instead of medical instruments) – perhaps the kinds used in manufacturing tend to have higher returns.

The higher estimated coefficients for the three structures types may be due to the fact that these are categories of structures not typically associated with manufacturing (as opposed to Industrial Buildings). A high investment share in one of them by a manufacturing firm may reflect that the firm is highly diversified. Therefore, the higher returns to these structures in manufacturing may reflect that diversified

[28] Table 7 has not yet been cleared for disclosure. It will be included in the next draft.

firms have higher productivity than non-diversified firms, whereas in nonmanufacturing, ownership of these structures does not indicate industrial diversity/scope.

# 6 Causality

As mentioned in Section 3, a common concern in production function estimation is simultaneity bias, which could arise if there is an unobserved productivity component that simultaneously affects the input decisions and the output realization. This is of particular concern in cross-sectional regressions since one cannot difference-out even non-time-varying unobserved productivity components. In this section, I present the results of a number of different approaches to alleviating this potential bias and/or to assessing the extent of the problem.

## 6.1 Analyzing how estimates vary over time

In addition to the regressions for 1998-2001, one can also estimate regressions for years prior to the investment composition decision. This allows one to assess whether the estimated relationship between capital mix and productivity is greater after the capital mix decision or before. The answer to this helps us determine which direction of causality dominates. Therefore, I estimate the cross-sectional production function regressions discussed above for 1995-1997, in addition to the 1998-2001 regressions.

Figure 1 shows the estimated coefficients over time for the three capital goods of most interest: Computers, Communications Equipment, and Software. The estimated coefficient for Communications Equipment is clearly higher after 1998 than before 1998, suggesting that the predominant direction of causality is from the investment decision to productivity. For software and computers, the estimates prior to 1998 are not much different from their values after 1998. This suggests that either investment shares for these capital goods are highly autocorrelated, there are important unobserved firm fixed effects (correlated with these capital types), or both. Below, I attempt to estimate firm "fixed" effects separately for the pre-1998 and post-1998 periods and evaluate whether their correlation with the investment shares is stronger in one period than the other.

First, though, it is worthwhile to take a moment to consider the time path of the coefficients in Figure 1 from 1998 onward. These paths may reflect the adjustment processes involved with the different capital types (though they may also reflect changes in organizational co-investments). The coefficient on Communications Equipment peaks in 1999 and then stays near that level through 2001 (at least). This may indicate that the investment immediately raises productivity and then, due to continued learning or adjustment, it continues to benefit productivity for a number of years. Software, on the other hand, peaks in 1998, suggesting that software may require less of an adjustment process.

## 6.2 "Fixed" Effects Before and After the Investment Decision

The results above indicate that unobserved firm fixed effects may be an important omitted variable in our regressions. Unfortunately, it is impossible to fully account for the potential effect of firm fixed effects with cross-sectional data. I do, however, have panel data for all of the variables in the model except the investment shares. Hence, it is possible to estimate firm fixed effects using the Compustat data, though obviously these fixed effects will not be orthogonal to capital mix.

These fixed effects should contain useful information. Consider estimating cross-sectional regressions of the form in equation (3) but without the investment shares. One can estimate such a cross-sectional regression separately for a number of years. The estimated residuals can be averaged over those years to obtain an estimate of the firm "fixed" effect for that period. "Fixed" is in quotations here as these effects are not, strictly speaking, fixed. Rather, they are persistent – changing period-to-period instead of year-to-year. The averaging has the advantage of removing some of the year-to-year noise in the data. The fixed effects, then, should capture slow-moving (persistent) and/or permanent firm factors that affect productivity (as measured). These factors include unobserved labor quality, workplace practices (e.g., HRM practices), co-investments, and other so-called "intangible capital." Lev and Radhakrishnan (2003), in fact, measure intangible capital in exactly this way, as the fixed effect from a production function estimation using Compustat data. Thus, an interesting question is whether these fixed effects are related to the capital mix and how. Furthermore, does capital mix have a greater relationship with the post-1998 fixed effect than it does with the pre-1998 effect, suggesting a causal link from capital mix to productivity? Finally, does capital mix affect the difference between the post-1998 and pre-1998 effects, suggesting a link from capital mix to productivity *growth*?

To answer these questions, first I estimate two sets of fixed effects, one for a period just before the 1998 observed investment mix decisions are made, 1995-97, and one for a period just after, 1999-2001. To estimate a period's fixed effect, I obtain the residuals, for each year, from the cross-sectional production function regression described above (equation 3), and then average the residuals, within firm, across the years of the period. I then regress each of these period's fixed effects on the 1998 investment shares.[29] If the permanent factors in intangible capital affect firms' capital mix decisions, then we should find statistically significant nonzero coefficients on investment shares in both of these two regressions. This finding would suggest that permanent factors have an effect on capital mix, though this does not preclude the possibility that capital mix has a causal effect on productivity as well. On the other hand, if we find that the investment shares are significantly larger in the latter period's regression, then it must be the case that the capital mix does indeed have a causal effect on productivity.

The results of these regressions are shown in Table 8. The first column of coefficient estimates are from a regression of the pre-1998 (1995-1997) fixed effect on each of the investment shares. As in the earlier regressions, Special Industry Machinery is the omitted category. A number of capital types have a statistically significant relationship with the pre-1998 fixed effect.

The fact that investment in 1998 in these types of capital are significantly related to productivity fixed effects in the pre-1998 period suggests that intangible capital (i.e., the slow-moving and permanent productivity factors captured by the fixed effects) does affect the investment composition decision. Not surprisingly, firms with high levels of intangible capital tend to subsequently invest in Computers, Software, Communications Equipment, and Offices – capital typically associated with innovative workplace practices, high labor quality, etc.. Such firms also appear to invest relatively more in General Purpose Machinery and Industrial Buildings.

The second column of estimates in Table 8 shows the results from regressing the

[29] Black and Lynch (2001) follow a similar approach in evaluating the impact of workplace practices on productivity, given a single year's data on workplace practices: First, they estimate a standard production function using establishment-level panel data and using the within or GMM estimator to account for the transmitted unobserved productivity component ($\omega_{it}$ in our model). They then average the residuals over the period 1987-93 to obtain establishment fixed effects. Lastly, they regress these fixed effects on firm-level measures of workplace practices (including human capital investments and computer usage) from a 1994 survey. My approach is an extension of this technique in that I perform the analysis for both a pre-survey period and a post-survey period in order to identify the direction of causality between the survey variables and productivity.

post-1998 (1999-2001) fixed effect on the investment shares. Most of the same capital types that were found to be associated with pre-1998 average productivity are found to be associated (in the same direction) with post-1998 average productivity. This suggests that there is an important permanent component in these fixed effects that is related to capital mix.

Comparing the pre-1998 results with the post-1998 results, notice that the post-1998 coefficients are greater for a number of capital types, though Software is a notable exception. In particular, Communications Equipment has a substantially greater coefficient in the post-1998 period than in the pre-1998 period. This suggests that, even though intangible capital/permanent productivity factors have an effect on the capital mix decision, capital mix, particularly the share of capital in communications equipment, has a *causal* effect on productivity. In other words, these results suggest that investment in communications equipment *raises* productivity.

So capital mix appears to affect the level of productivity. But does capital mix affect productivity *growth*? To answer this question, I regress the difference between the post-1998 effect and the pre-1998 fixed effects on the investment shares. This difference represents the (percentage) jump in productivity between the pre-1998 period and the post-1998 period. The estimated coefficients on the investment shares are shown in the last column of Table 8.

I find that, as was the case regarding the average productivity levels, both Computers and Communications Equipment are positively and significantly related to the growth in productivity between the two periods. Autos, Commercial Buildings, Utility Structures, and Other Structures are also positively and significantly related to productivity growth. Offices, on the other hand, are found to be negatively and significantly related to productivity growth.

This OLS regression of the difference in fixed effects on investment shares cannot control for the possibility of reverse causality. For instance, it is possible that there was some omitted dynamic factor that affected productivity growth between the pre-1998 and post-1998 periods and simultaneously affected the capital mix (e.g., a new CEO hired in 1998). Nonetheless, it seems likely that at least part of the effect of capital mix on productivity growth is causal.

## 6.3 Proxying for Unobserved Productivity Shocks

Given the above evidence that the baseline results may be affected by unobserved productivity components that are known ("transmitted") to the firm ex-ante, in this subsection I discuss two techniques that attempt to directly control for the unobserved component in the regression.

### 6.3.1 Olley-Pakes Approach

One technique to address simultaneity bias is that proposed by Olley and Pakes (1996). They demonstrate that under certain conditions, the unobserved productivity shock, $\omega_{it}$, may be proxied by a function of current investment, capital stock, and age (and their cross-terms). That is, $\omega_{it} = g(I_{it}, k_{it}, age_{it})$. They suggest using a kernel estimator or a 3rd-order polynomial to approximate $g()$.

Thus, as a robustness check on our results, I include a third-order polynomial of $I$, $k$, and $age$ (including cross-terms) in addition to the other regressors. I find that this addition has virtually no effect on the results, though the output elasticities with respect to labor and capital do move slightly closer to their factor shares.[30]

### 6.3.2 Future MFP as a proxy for unobserved productivity

In a similar spirit, another possible method for accounting for the unobserved, transmitted productivity component is to include a measure of future productivity in the contemporaneous regression. If productivity shocks, $\omega_{it}$, are serially correlated, future productivity may serve as an indicator of current productivity. In addition, future productivity may reflect the fixed productivity component, $f_i$, as well, so that future productivity may be an indicator of the entire transmitted productivity component, $\omega_{it} + f_i$. The drawback of this approach is that if future productivity is caused, in part, by the current capital mix, then including future productivity will introduce multicollinearity and thereby reduce the precision of the estimators of $\{\theta_p\}$. As a robustness check on the baseline results, though, this drawback becomes an advantage as it reduces the likelihood of falsely obtaining statistically significant estimates of $\{\theta_p\}$.

To implement this approach, I include $2fp_{t+1}$ as an additional regressor in the

[30] These results are considered a robustness check rather than as part of the baseline results since other studies have shown that the Olley-Pakes conditions may frequently be violated in practice. See, e.g., [33]. The results of these regressions are available from the author upon request.

regressions for $t$ =1998-2000. The estimated coefficients on the investment shares are not materially affected.[31] As expected given the likelihood of introducing multicollinearity, the standard errors on these coefficients are increased somewhat, but nevertheless, Computers, Communications Equipment, Software, and Offices remain positively and significantly associated with current productivity, with little change in the value of their coefficients. An exception is that Software is no longer significant in the 1998 regression, though it remains significant at the 99% level is the 1999 and 2000 regressions. The only other notable change is that General Purpose Machinery now becomes significant (positive) in the 1999 regression (at the 99% level) and the 2000 regression (at the 90% level). It is also interesting to note that the coefficients on capital and labor move much closer to their average factor shares, as was also the case in the results from the Olley-Pakes approach.

# 7 Complementarities and Substitutabilities

The results presented thus far establish that the standard measure of capital stock used in micro-level production functions does not adequately account for capital mix. But these results do not shed light on the fundamental question of whether it is possible at all to express capital as a single aggregate. That is, are capital goods perfectly substitutable? To answer this question, one must test whether certain "bundles" – i.e., pairs, triples, quadruples, etc., of different types of capital have an impact on productivity above and beyond the individual effects that each type of capital have on productivity. In the standard Neoclassical production model, the cross-partial derivative for any pair of capital goods is equal to zero: $F_{pj} = 0$ for $p \neq j$. This restriction can be straightforwardly tested with the ACES data.

Starting with the production function regressions discussed above (results for which are shown in Table 3), I add interactions of investment shares between every possible pair (dyad) of capital types in our data. With 20 types, this amounts to 190 interactions.[32] [Results are now shown for space considerations. Contact author for actual estimates.] I note first that the investment shares for Computers, Commu-

[31] The results for these regressions are available from the author upon request.

[32] The number of dyads in a 20-member set is $(20 \times 19)/2 = 190$. In general, the number of $n$-ads in a $G$-member set is $G!/[n!(G-n)!]$. Using this formula, one can see that adding triad or higher-$n$ interactions, though they may have interesting real effects, would rapidly use up all of the degrees of freedom in our regressions.

nications Equipment, Software, and Office Buildings remain statistically significant, at least from 1999 onward, even after the inclusion of these interactions. I find a number of significant interactions, which implies that returns (and marginal products) for particular capital goods are affected by the presence of other complimentary or substitutable capital goods.[33] This result is a rejection of the perfect substitutability assumption necessary for the existence of a single capital aggregate (in a world with embodied technological change).[34]

It is worth highlighting a few of the most notable complementarities and substitutabilities.[35] Computers and Fabricated Metal Products are found to be complementary in three of the four years (1999 is the exception), as are Instruments and Fabricated Metal Products. This suggests that traditional, "low-tech" metal products like hand tools, valves, pipes, springs, wires, storage tanks, etc., are made more productive through the use of "high-tech" Computers and Instruments. Instruments are also found to interact positively with Other Transportation Equipment. Other Transportation Equipment, in turn, is found to interact negatively with Fabricated Metal Products. Another finding is that Commercial Buildings are complementary

[33] The p-value on an F-test of the hypothesis that all interactions are jointly equal to zero is less than 0.001 for all four yearly regressions.

[34] Without embodied technology, capital subaggregates need not necessarily be perfectly substitutable for the existence of a single capital aggregate, $K = g(K_1, K_2)$; the necessary condition is that the marginal rate of substitution between the subaggregate be independent of labor (Solow (1955-1956)). Solow commented that this condition "will not often be even approximately satisfied in the real world." With embodied technology, not only must this condition hold, but additionally the subaggregates must be perfectly substitutable (Fisher (1965)).

[35] The following interactions were found to be significant at the 95% level or higher (the sign and significance level of their coefficient is in parentheses):

Computers & Fabricated Metal Products (+, 5%), Computers & Commercial Buildings (+, 1%), Other Office Eqp. & Aircraft (+, 1%), Other Office Eqp. & Misc. Eqp. (-, 5%), Other Office Eqp. & Other Structures (-, 1%), Communications Eqp. & Industrial Buildings (-, 1%), Software & Aircraft (-, 1%), Software & Other Transportation Eqp. (+, 5%), Fabricated Metal Products & Other Transportation Eqp. (-, 1%), Fabricated Metal Products & Instruments (+, 1%), Fabricated Metal Products & Commercial Buildings (-, 1%), Metalworking Machinery & Autos (-, 1%), Metalworking Machinery & Other Transportation Eqp. (+, 1%), Autos & Trucks (+1%), Autos & Elec. Eqp. (-5%), Other Transportation Eqp. & Instruments (+ , 5%), Other Transportation Eqp. & Misc. Eqp. (+, 5%), Misc. Eqp. & Commercial Buildings (-, 5%), Commercial Buildings & Industrial Buildings (+, 5%), Utility Structures & Other Structures (+, 5%), Utility Structures & Industrial Buildings (+, 1%), Office Buildings & Industrial Buildings (-, 5%), Special Industry Machinery & Office Buildings (+, 5%).

with Computers but substitutable (to some extent) with Fabricated Metal Products.

In general, the findings appear to yield a very interesting set of patterns:

(1) "high-tech" capital tends to be complementary with "low-tech" capital,

(2) "high-tech" capital tends to be substitutable with other "high-tech" capital,

(3) "low-tech" capital tends to be substitutable with other "low-tech" capital.

These patterns are true if one groups Computers, Communications Equipment, Software, Instruments, Electrical Equipment, Metalworking Machinery[36], Autos, Aerospace, and Special Industry Machinery[37] into "high-tech" and Other Office Equipment, Fabricated Metal Products, Heavy Duty Trucks, Other Transportation Equipment, and all types of Structures into "low-tech" (with General Purpose Machinery somewhere in between). These classifications are not arbitrary. They would be obtained, almost exactly, if one split the list of capital types on the basis of how much R&D expenditures are applied to each capital type in the U.S. (See Wilson (2002), who compiled such a list from NSF data). The classifications would also be obtained to a large extent if one split the list according to the implied marginal products (or, for that matter, the official BLS user costs) in Table 6 (exceptions are that Aircraft would become low-tech while Miscellaneous Equipment, Office Equipment, and Office Buildings would become high-tech).

To confirm these patterns more formally, I estimate the same model but restricting the coefficients to be equal within each of the following three groups: (1) pairs of high-tech goods, (2) pairs of low-tech goods, (3) pairs with one high-tech good and one low-tech good (using the high-tech/low-tech classification above[38]).

The results are shown in Table 9. As expected, interactions within the high-tech/high-tech group are found to be negative (substitutes) on average, as are those within the low-tech/low-tech group, while interactions between high-tech and low-tech goods are found to be positive (complements) on average. The coefficient on the high-tech/high-tech interactions is statistically significantly negative (at the 90% level

[36]For a discussion of recent major innovations in Metalworking Machinery used for valve-making (e.g., Computerized Numerical Control machines), see Bartel, Ichniowski, and Shaw (2004a, 2004b).

[37]As the name suggests, Special Industry Machinery is a hodge-podge of heterogeneous equipment, some of which are better described as "low-tech" (e.g., circular saws) and some of which are better described as "high-tech" (e.g., Semiconductor wafer processing eqp.). Hence, this type could arguably go into either category.

[38]General Purpose Machinery was assigned to the low-tech group for the regressions whose results are shown, though assigning it to high-tech yielded similar results.

or higher) in all four year 1998-2001 and the coefficient on the high-tech/low-tech interactions is statistically significantly positive in all years except 2000 (though the p-value is only 0.119). The coefficient on the low-tech/low-tech interactions, though, is not statistically significant in any of the years. Nonetheless, the point estimates of this coefficient are fairly large and the p-values are just barely above 10% in two out of the four years (the p-values for 1998-2001 are 0.102, 0.73, 0.226, and 0.105, respectively).

These findings are consistent with the basic intuition that the more similar a pair of goods are, the more substitutable they are. Presumably, high-tech capital goods are more similar to each other than to low-tech goods. On the other hand, a number of authors have argued that high-tech investments such as computers tend to be part of a system of co-investments in complementary goods, some tangible and some intangible (Brynjolfsson & Hitt 1997, 2002; Bresnahan, Brynjolfsson, and Hitt (2000)). In particular, one might have expected computers and software to have been found to be complementary. That they are not (though they are not found to be substitutes either) may reflect the fact that computers typically already embody a large amount of software the day they are purchased, hence firms may choose to some extent between buying additional computers with the available pre-loaded software or buying new software for their existing computers.[39] These two scenarios need not be complementary. A similar argument may apply to the relationship between computers and communications equipment.

In sum, contrary to common perceptions, the data suggest that high-tech capital goods are not in fact complementary with each other, but rather they are complementary with low-tech equipment and structures.

# 8 Conclusion

This paper has shown that, for a number of capital goods, including ICT capital, investment is associated with higher productivity. Moreover, though there is evidence that slow-moving firm-specific factors – often referred to as "intangible capital" – tend to be co-investments with these capital goods, at least part of the association appears to be causal. These results support the growing consensus that ICT's have had a positive impact on total-factor productivity in recent years. They also show that this

[39] Recall that the software category in ACES, as in the NIPAs, excludes software that is embedded in hardware.

conclusion is robust to controlling for other simultaneous capital investments.

Given the purely cross-sectional nature of the disaggregate investment data from the 1998 ACES, however, it is impossible to fully disentangle the effect of investment/capital mix on productivity from possible feedback in the opposite direction. Plans for some future ACES surveys call for such disaggregate investment detail to be collected again, which may allow future research to better address this issue (as well as other issues).

The paper also finds evidence of complementarities and substitutabilities among different capital goods. In particular, the predominant pattern of the results suggests that goods typically classified as "high-tech" tend to be complements with "low-tech" goods and substitutes with other "high-tech" goods (and similarly for "low-tech" goods). This pattern is quite sensible from an economic point of view, though it contrasts with the prevailing popular view that high-tech capital goods are generally complementary to each other. The best explanation for this discrepancy is that the high-tech goods considered in this paper often already embed many of the characteristics that are generally associated with many of the other high-tech goods.

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# 10 Appendix A – Variable construction

The following is a list of the key variables used in this paper and how they were constructed from the data at hand:

**Real Output** – Real Output is obtained by dividing Compustat's sales variable (SALES_NET – #A12) by the BEA's 3-digit SIC level gross output deflator (P): Y = SALES_NET/P.

**Total capital** – Total capital (K) is obtained by deflating Compustat's Property, Plant, and Equipment (Total - Gross) (PPEGT) by the BLS's 2-digit total investment deflators. Following Brynjolfsson and Hitt (2003), the deflator is applied at the calculated average age of capital, based on a 3-year (t, t-1, t-2) average of the ratio of total accumulated depreciation (ACC_DEPR) to current depreciation (Depreciation and Amortization: DP). ACC_DEPR is calculated as Property, Plant, and Equipment (Total - Gross) minus Property, Plant & Equipment (Total - Net): ACC_DEPR = PPEGT - PPENT. A preferable method for measuring the capital stock would have been the perpetual inventory method. However, the necessary long time series of past annual investment is not available. Fortunately, it has been shown that the book value capital stock yields virtually identical results in production function regressions to perpetual inventory capital stock.[40]

**Labor** – The labor input (L) is measured as the number of employees (EMP) reported in Compustat.

**Wages** and **Labor Costs** – For a subset of firms, Compustat provides data on Labor and Related Expenses (XLR). For these firms, the average wage can be obtained by dividing XLR by EMP. For firms with missing values for XLR, I impute the average wage by multiplying the firm's number of employees (EMP) by the 3-digit industry mean of average wages, computed over firms with nonmissing values for XLR. If there 2 or fewer firms with nonmissing XLR in that 3-digit industry, I use the 2-digit industry mean. XLR for firms with missing values is then imputed by taking the product of the imputed average wage and the reported value of EMP.

**Nominal Materials Costs** – Nominal materials (PM) are calculated (using Compustat) as sales net of Operating Income Before Depreciation (OIDBP) and Labor and Related Expenses (XLR):

PM = SALES_NET - OIDBP - XLR.

An equivalent definition is Cost of Goods Sold (COGS) plus Selling, General, and Administrative Expense (XSGA) minus XLR:

PM = COGS + XSGA - wL.

The two definitions are equivalent since OIDBP is defined as SALES_NET-COGS-XSGA. I use the first definition unless it yields a missing value in which case I use the second definition.

**Real Materials Costs** – Real materials costs (M) are calculated as nominal

[40] See Becker, Haltiwanger, Jarmin, Klimek, and Wilson (2004).

materials (PM) deflated by the BEA's 3-digit gross output deflator (P). Unfortunately, no separate deflator exists that is specific to materials.

**2-factor productivity** – The natural log of 2-factor productivity (2FP), which is the dependent variable in the 2FP regressions, is computed using the following formula:

$$2FP = y - \left(\frac{rK}{PY}\right) k - \left(\frac{wL}{PY}\right) \ell$$

where $y$, $k$, and $\ell$ are the logs of real output (Y), total capital (K), and labor (L) (all defined above). $r$ is the capital rental price, obtained at the 2-digit SIC level from the BLS. $wL$ comes from Compustat's variable, Labor and Related Expenses (XLR). As discussed in Section 3, as a robustness check, I also use an alternative measure of 2FP where Y is replaced by double-deflated value added (VA): VA = Y - M.

**3-factor productivity** – Similar to $2FP$, the natural log of 3-factor productivity (3FP) is computed as:

$$3FP = y - \left(\frac{rK}{PY}\right) k - \left(\frac{wL}{PY}\right) \ell - \left(\frac{PM}{PY}\right) m$$

where $y$, $k$, $\ell$ and $m$ are the natural logs of output, capital, labor, and materials, respectively.

**Investment Spike** – The investment spike dummy variable (SPIKE) is 1 if current total investment is equal to or greater than 20% of K; 0 otherwise.

**Employment Size** – The employment size class indicator (SIZE) can take on five values:

SIZE = 1 if L $<$ 1000

SIZE = 2 if 1000 $\leq$ L $<$ 2000

SIZE = 3 if 2000 $\leq$ L $<$ 4500

SIZE = 4 if 4500 $\leq$ L $<$ 11500

SIZE = 5 if 11500 $\leq$ L

| TABLE 1. ACES asset types and aggregated categories used in regressions | | |
|---|---|---|
| Original ACES Asset Type Codes | Description | Aggregated Category Names |
| **Equipment** | | |
| 311 | Computer and Peripheral Equipment | Computers |
| 312 | Office Equipment Except Computers and Peripherals | Office Equipment |
| 313 | Communications, Audio, and Video Equipment | Communications and AV Equipment |
| 314 | Navigational, Measuring, Electromedical, and Control Instruments | Instruments |
| 315 | Medical Equipment and Supplies | |
| 316 | Capitalized Software Purchased Separately | Software |
| 321 | Fabricated Metal Products | Fabricated Metal Products |
| 322 | Metalworking Machinery | Metalworking Machinery |
| 323 | Special Industrial Machinery | Special Industrial Machinery |
| 324 | Ventilation, Heating, Air-Conditioning, Commercial Refrigeration, and Other General Purpose Machinery | General Purpose Machinery |
| 331 | Cars and Light Trucks | Autos |
| 332 | Heavy Duty Trucks | Trucks |
| 333 | Aerospace Products and Parts | Aircraft |
| 334 | Other Transportation Equipment | Other Transportation Equipment |
| 341 | Engine, Turbine, and Power Transmission Equipment | Electrical Equipment |
| 342 | Electrical Transmission and Distribution Equipment | |
| 343 | Electrical Equipment, NEC | |
| 344 | Mining and Oil and Gas Field Machinery and Equipment | Miscellaneous Equipment |
| 345 | Floating Oil and Gas Drilling and Production Platforms | |
| 346 | Nuclear Fuel | |
| 351 | Furniture and Related Products | |
| 352 | Agricultural Equipment | |
| 353 | Construction Machinery | |
| 354 | Service Industry Equipment | |
| 355 | Other Miscellaneous Equipment | |
| 361 | Artwork, Books, and Other Equipment, NEC | |

| TABLE 1 continued… | | |
|---|---|---|
| **Structures** | | |
| 131 | Manufacturing, Processing, and Assembly Plants | Industrial Buildings |
| 132 | Industrial Nonbuilding Structures | |
| 141 | Office, Bank, and Professional Buildings | Offices |
| 142 | Medical Offices | |
| 151 | Automotive Facilities | Commercial Buildings |
| 152 | Stores - Food Related | |
| 153 | Multi-Retail Stores | |
| 154 | Warehouses and Distribution Centers (except Passenger) | |
| 155 | Other Commercial Stores/Buildings, NEC | |
| 161 | Hospitals | |
| 162 | Special Care Facilities | |
| 171 | Amusement and Recreational Facilities | |
| 181 | Air, Land, and Water Transportation Facilities | Utility Structures |
| 191 | Telecommunication Facilities | |
| 192 | Electric, Nuclear, and Other Power Facilities | |
| 193 | Water Supply, Sewage, and Waste Disposal Facilities | |
| 111 | Residential Structures | Other Structures |
| 112 | Manufactured (Mobile) Homes | |
| 121 | Hotels, Motels, and Inns | |
| 201 | Preschool, Primary/Secondary, and Higher Education Facilities | |
| 202 | Special School and Other Educational Facilities | |
| 203 | Religious Buildings | |
| 204 | Public Safety Buildings | |
| 211 | Mine Shafts | |
| 212 | Petroleum and Natural Gas Wells | |
| 213 | Other Mining and Well Construction | |
| 221 | Conservation and Control Structures | |
| 222 | Highway and Street Structures | |
| 223 | Other Non-building Structures, NEC | |

## Table 2 -- Summary Statistics

| Variable | Mean | Standard Deviation | Correlation with Sales[1] |
|---|---|---|---|
| Sales | 2377 | 6770 | 1.000 |
| K | 1835 | 6960 | 0.788 |
| L | 12.559 | 38.163 | 0.690 |
| Spike | 0.289 | 0.453 | -0.031 |
| Size Class1 | 0.153 | 0.360 | |
| Size Class2 | 0.185 | 0.388 | |
| Size Class3 | 0.227 | 0.419 | |
| Size Class4 | 0.211 | 0.408 | |
| Size Class5 | 0.224 | 0.417 | |
| Computer and Peripheral Equipment | 0.151 | 0.221 | 0.001 |
| Office Equipment Except Computers and Peripherals | 0.018 | 0.070 | -0.010 |
| Communications, Audio, and Video Equipment | 0.029 | 0.114 | 0.041 |
| Capitalized Software Purchased Separately | 0.033 | 0.093 | -0.041 |
| Fabricated Metal Products | 0.015 | 0.085 | -0.024 |
| Metalworking Machinery | 0.066 | 0.188 | -0.039 |
| Special Industrial Machinery | 0.162 | 0.280 | -0.025 |
| General Purpose Machinery | 0.044 | 0.135 | -0.013 |
| Cars and Light Trucks | 0.015 | 0.070 | 0.153 |
| Heavy Duty Trucks | 0.010 | 0.068 | -0.013 |
| Aerospace Products and Parts | 0.012 | 0.092 | 0.041 |
| Other Transportation Equipment | 0.015 | 0.084 | -0.013 |
| Industrial Equipment | 0.083 | 0.143 | 0.021 |
| Office Buildings | 0.046 | 0.118 | -0.016 |
| Commercial Buildings | 0.088 | 0.194 | 0.025 |
| Utilities | 0.038 | 0.152 | 0.004 |
| Other Structures | 0.027 | 0.129 | 0.014 |
| Instruments | 0.017 | 0.083 | -0.024 |
| Electrical Equipment | 0.023 | 0.119 | 0.017 |
| Miscellaneous Equipment | 0.107 | 0.192 | 0.017 |
| Number of Equipment Types | 4.589 | 3.182 | |
| Number of Structure Types | 1.666 | 1.185 | |
| Number of Observations | 1461 | | |

[1]Partial correlations controlling for 3-digit SIC industry dummy variables.

**Table 3 -- Production Function Regressions**

| | (1) 1998 | (2) 1999 | (3) 2000 | (4) 2001 |
|---|---|---|---|---|
| | Coef. Estimate | Coef. Estimate | Coef. Estimate | Coef. Estimate |
| Investment Shares: | | | | |
| Aircraft | -0.01 (0.16) | -0.33 (0.20) | -0.44 (0.21) ** | -0.21 (0.21) |
| Autos | 0.40 (0.40) | 0.44 (0.47) | 0.37 (0.39) | 0.50 (0.36) |
| Commercial Buildings | -0.02 (0.15) | -0.06 (0.16) | -0.27 (0.16) * | -0.19 (0.15) |
| Communications and AV Equipment | 0.47 (0.21) ** | 0.81 (0.25) *** | 0.80 (0.25) *** | 0.74 (0.30) ** |
| Computers | 0.55 (0.10) *** | 0.57 (0.11) *** | 0.47 (0.12) *** | 0.47 (0.12) *** |
| Electrical Equipment | -0.15 (0.17) | -0.13 (0.21) | -0.12 (0.21) | 0.12 (0.20) |
| Fabricated Metal Products | -0.04 (0.13) | -0.06 (0.14) | 0.04 (0.17) | 0.05 (0.17) |
| General Purpose Machinery | 0.11 (0.10) | 0.13 (0.10) | 0.21 (0.13) * | 0.28 (0.13) ** |
| Industrial Buildings | 0.20 (0.11) * | 0.22 (0.12) * | 0.07 (0.13) | 0.19 (0.13) |
| Instruments | 0.17 (0.16) | 0.07 (0.18) | -0.12 (0.20) | -0.11 (0.19) |
| Metalworking Machinery | 0.09 (0.08) | 0.03 (0.09) | -0.01 (0.10) | 0.02 (0.09) |
| Miscellaneous Equipment | 0.11 (0.10) | 0.09 (0.11) | -0.04 (0.11) | 0.01 (0.11) |
| Office Equipment | 0.15 (0.24) | 0.14 (0.25) | 0.08 (0.28) | 0.05 (0.29) |
| Offices | 0.56 (0.17) *** | 0.49 (0.17) *** | 0.54 (0.19) *** | 0.52 (0.20) *** |
| Other Structures | -0.12 (0.16) | 0.14 (0.20) | -0.14 (0.22) | 0.06 (0.22) |
| Other Transportation Equipment | -0.04 (0.22) | -0.23 (0.25) | -0.18 (0.25) | 0.04 (0.25) |
| Software | 0.93 (0.22) *** | 0.76 (0.23) *** | 0.63 (0.20) *** | 0.65 (0.19) *** |
| Trucks | -0.05 (0.28) | -0.16 (0.29) | -0.20 (0.27) | -0.15 (0.27) |
| Utility Structures | -0.07 (0.15) | -0.17 (0.20) | -0.02 (0.19) | 0.26 (0.18) |
| Other Variables: | | | | |
| log(emp) | 0.53 (0.05) *** | 0.53 (0.05) *** | 0.52 (0.04) *** | 0.49 (0.05) *** |
| log(k) | 0.41 (0.02) *** | 0.43 (0.02) *** | 0.45 (0.03) *** | 0.44 (0.03) *** |
| Size Class2 | -0.04 (0.06) | -0.10 (0.07) | -0.05 (0.07) | -0.01 (0.07) |
| Size Class3 | 0.02 (0.07) | -0.03 (0.08) | -0.02 (0.08) | 0.03 (0.09) |
| Size Class4 | -0.02 (0.10) | -0.07 (0.10) | -0.03 (0.09) | 0.04 (0.11) |
| Size Class5 | 0.08 (0.14) | -0.05 (0.15) | -0.07 (0.14) | 0.07 (0.17) |
| Spike dummy | 0.07 (0.04) ** | 0.08 (0.04) * | 0.06 (0.04) | 0.04 (0.04) |
| Constant | 3.62 (0.17) *** | 3.11 (0.19) *** | 3.36 (0.22) *** | 3.09 (0.21) *** |
| Number of Observations | 1448 | 1358 | 1265 | 1283 |
| R-Sq | 0.9109 | 0.8968 | 0.9004 | 0.9041 |

Notes: These regressions also include 3-digit SIC industry dummies and state dummies, though due to confidentiality concerns, the coefficients on these dummies are not shown.
Robust standard errors are shown in parentheses.
*** denotes significance at the 99% level
** denotes significance at the 95% level
* denotes significance at the 90% level

**Table 4 -- Labor Productivity Regressions**

| | 1998 | 1999 | 2000 | 2001 |
|---|---|---|---|---|
| Variable | Coef. Estimate | Coef. Estimate | Coef. Estimate | Coef. Estimate |
| Investment Shares: | | | | |
| Aircraft | -0.05 (0.14) | -0.34 (0.20) * | -0.44 (0.21) ** | -0.25 (0.22) |
| Autos | 0.37 (0.40) | 0.43 (0.47) | 0.35 (0.38) | 0.44 (0.36) |
| Commercial Buildings | -0.03 (0.15) | -0.06 (0.16) | -0.27 (0.16) * | -0.20 (0.15) |
| Communications and AV Equipment | 0.45 (0.22) ** | 0.80 (0.25) *** | 0.79 (0.25) *** | 0.74 (0.32) ** |
| Computers | 0.54 (0.10) *** | 0.57 (0.11) *** | 0.47 (0.12) *** | 0.47 (0.12) *** |
| Electrical Equipment | -0.17 (0.17) | -0.14 (0.21) | -0.12 (0.20) | 0.12 (0.20) |
| Fabricated Metal Products | -0.03 (0.13) | -0.06 (0.14) | 0.04 (0.17) | 0.04 (0.17) |
| General Purpose Machinery | 0.10 (0.10) | 0.14 (0.10) | 0.21 (0.13) * | 0.27 (0.13) ** |
| Industrial Buildings | 0.19 (0.11) * | 0.21 (0.12) * | 0.07 (0.13) | 0.17 (0.13) |
| Instruments | 0.17 (0.16) | 0.08 (0.18) | -0.11 (0.20) | -0.08 (0.18) |
| Metalworking Machinery | 0.08 (0.08) | 0.03 (0.09) | -0.01 (0.10) | 0.02 (0.09) |
| Miscellaneous Equipment | 0.10 (0.10) | 0.09 (0.11) | -0.04 (0.11) | 0.01 (0.10) |
| Office Equipment | 0.13 (0.23) | 0.13 (0.25) | 0.08 (0.28) | 0.04 (0.29) |
| Offices | 0.57 (0.17) *** | 0.50 (0.17) *** | 0.54 (0.19) *** | 0.51 (0.19) *** |
| Other Structures | -0.11 (0.16) | 0.14 (0.19) | -0.14 (0.21) | 0.06 (0.22) |
| Other Transportation Equipment | -0.04 (0.21) | -0.23 (0.25) | -0.19 (0.25) | 0.03 (0.24) |
| Software | 0.93 (0.22) *** | 0.75 (0.23) *** | 0.63 (0.20) *** | 0.64 (0.20) *** |
| Trucks | -0.05 (0.27) | -0.16 (0.29) | -0.21 (0.27) | -0.14 (0.26) |
| Utility Structures | -0.08 (0.14) | -0.17 (0.20) | -0.02 (0.18) | 0.26 (0.18) |
| Other Variables: | | | | |
| Capital-Labor ratio | 0.41 (0.02) *** | 0.43 (0.02) *** | 0.45 (0.03) *** | 0.44 (0.03) *** |
| Size Class2 | -0.10 (0.05) * | -0.14 (0.06) ** | -0.08 (0.07) | -0.09 (0.06) |
| Size Class3 | -0.08 (0.05) | -0.09 (0.06) | -0.06 (0.07) | -0.09 (0.06) |
| Size Class4 | -0.17 (0.06) *** | -0.15 (0.06) ** | -0.10 (0.07) | -0.14 (0.06) ** |
| Size Class5 | -0.14 (0.05) *** | -0.19 (0.06) *** | -0.18 (0.06) *** | -0.22 (0.06) *** |
| Spike dummy | 0.07 (0.04) ** | 0.08 (0.04) ** | 0.06 (0.04) | 0.04 (0.04) |
| Constant | 3.67 (0.16) *** | 3.12 (0.19) *** | 3.37 (0.22) *** | 3.18 (0.20) *** |
| | | | | |
| Number of Observations | 1448 | 1358 | 1265 | 1283 |
| R-Sq | 0.6778 | 0.6427 | 0.6433 | 0.6525 |

Notes: These regressions also include 3-digit SIC industry dummies and state dummies, though due to confidentiality concerns, the coefficients on these dummies are not shown.

Robust standard errors are shown in parentheses.

*** denotes significance at the 99% level

** denotes significance at the 95% level

* denotes significance at the 90% level

**Table 5 -- 2FP Regressions**

| | 1998 | 1999 | 2000 | 2001 |
|---|---|---|---|---|
| Variable | Coef. Estimate | Coef. Estimate | Coef. Estimate | Coef. Estimate |
| Investment Shares: | | | | |
| Aircraft | 0.26 (0.72) | 0.31 (0.82) | 0.22 (0.86) | -0.38 (1.06) |
| Autos | 0.61 (0.88) | 0.42 (1.09) | 1.17 (0.85) | 1.00 (0.94) |
| Commercial Buildings | 0.50 (0.39) | 0.28 (0.37) | -0.01 (0.39) | -0.14 (0.38) |
| Communications and AV Equipment | 0.73 (0.49) | 1.19 (0.54) ** | 2.07 (0.57) *** | 1.31 (0.43) *** |
| Computers | 1.01 (0.27) *** | 0.88 (0.28) *** | 0.65 (0.31) ** | 0.46 (0.33) |
| Electrical Equipment | -0.68 (0.50) | -0.37 (0.66) | -0.61 (0.74) | 0.20 (0.54) |
| Fabricated Metal Products | -0.28 (0.39) | -0.58 (0.44) | -0.73 (0.50) | -0.41 (0.47) |
| General Purpose Machinery | 0.47 (0.30) | 0.24 (0.32) | 0.39 (0.36) | 0.81 (0.33) ** |
| Industrial Buildings | 0.37 (0.35) | 0.48 (0.34) | 0.07 (0.41) | 0.46 (0.40) |
| Instruments | 0.41 (0.51) | 0.06 (0.54) | -0.42 (0.64) | -0.51 (0.58) |
| Metalworking Machinery | 0.12 (0.23) | 0.02 (0.25) | -0.17 (0.26) | -0.15 (0.27) |
| Miscellaneous Equipment | -0.03 (0.27) | -0.14 (0.30) | -0.72 (0.33) ** | -0.45 (0.32) |
| Office Equipment | 0.26 (0.48) | 0.28 (0.52) | 0.05 (0.53) | -0.13 (0.54) |
| Offices | 1.03 (0.44) ** | 1.39 (0.45) *** | 1.18 (0.52) ** | 1.34 (0.54) ** |
| Other Structures | -0.84 (0.62) | 0.67 (0.56) | -0.34 (0.70) | 0.33 (0.77) |
| Other Transportation Equipment | 0.50 (0.70) | -0.53 (0.75) | -0.13 (0.80) | 0.39 (0.76) |
| Software | 1.89 (0.55) *** | 2.19 (0.48) *** | 1.64 (0.48) *** | 1.55 (0.48) *** |
| Trucks | 0.65 (0.76) | 0.15 (0.80) | -0.18 (0.80) | -0.17 (0.77) |
| Utility Structures | -0.34 (0.49) | -0.03 (0.48) | 0.06 (0.58) | 0.53 (0.50) |
| Other Variables: | | | | |
| Size Class2 | 0.56 (0.13) *** | 0.42 (0.14) *** | 0.48 (0.14) *** | 0.65 (0.15) *** |
| Size Class3 | 1.03 (0.12) *** | 1.08 (0.14) *** | 1.10 (0.15) *** | 1.24 (0.15) *** |
| Size Class4 | 1.46 (0.13) *** | 1.46 (0.15) *** | 1.54 (0.15) *** | 1.61 (0.16) *** |
| Size Class5 | 2.46 (0.13) *** | 2.46 (0.14) *** | 2.46 (0.15) *** | 2.51 (0.16) *** |
| Spike dummy | 0.07 (0.09) | 0.05 (0.10) | 0.00 (0.11) | 0.04 (0.10) |
| Constant | 3.67 (0.40) *** | 2.85 (0.46) *** | 3.82 (0.56) *** | 2.65 (0.61) *** |
| | | | | |
| Number of Observations | 1403 | 1309 | 1226 | 1242 |
| R-Sq | 0.4980 | 0.4958 | 0.4754 | 0.4621 |

Notes: These regressions also include 3-digit SIC industry dummies and state dummies, though due to confidentiality concerns, the coefficients on these dummies are not shown.
Robust standard errors are shown in parentheses.
*** denotes significance at the 99% level
** denotes significance at the 95% level
* denotes significance at the 90% level

**Table 6 -- Marginal Products Implied by Estimated Coefficients (1998)**

| | Implied Marginal Product[1] | | | | |
|---|---|---|---|---|---|
| Capital Type | (1) Production Function | (2) Labor Productivity | (3) 2FP | Official (BLS) rental price/user cost | Depreciation ratio[2] |
| Aircraft | 0.14 | 0.13 | 0.22 | 0.15 | 0.85 |
| Autos | 0.57 | 0.55 | 0.81 | 0.41 | 3.11 |
| Commercial Buildings | 0.14 *** | 0.14 *** | 0.17 *** | 0.10 | 0.13 |
| Communications and AV Equipment | 0.27 * | 0.27 * | 0.34 | 0.16 | 0.78 |
| Computers | 0.61 ** | 0.60 ** | 1.00 ** | 0.41 | 2.43 |
| Electrical Equipment | 0.11 | 0.10 | -0.02 | 0.14 | 0.72 |
| Fabricated Metal Products | 0.14 | 0.14 | 0.08 | 0.15 | 0.68 |
| General Purpose Machinery | 0.17 | 0.17 | 0.27 | 0.15 | 0.78 |
| Industrial Buildings | 0.16 *** | 0.16 *** | 0.17 ** | 0.11 | 0.21 |
| Instruments | 0.22 | 0.22 | 0.32 | 0.20 | 1.20 |
| Metalworking Machinery | 0.17 | 0.17 | 0.18 | 0.16 | 0.87 |
| Miscellaneous Equipment | 0.20 | 0.20 | 0.13 | 0.21 | 1.48 |
| Office Equipment | 0.28 | 0.27 | 0.39 | 0.32 | 2.66 |
| Offices | 0.18 *** | 0.18 *** | 0.21 *** | 0.10 | 0.18 |
| Other Structures | 0.13 *** | 0.13 *** | 0.06 | 0.09 | 0.30 |
| Other Transportation Equipment | 0.14 | 0.14 | 0.22 | 0.09 | 0.45 |
| Software | 1.37 *** | 1.37 *** | 2.63 *** | 0.48 | 3.76 |
| Trucks | 0.12 | 0.12 | 0.47 | 0.24 | 1.43 |
| Utility Structures | 0.14 *** | 0.14 *** | 0.12 * | 0.05 | 0.22 |

[1]Calculated as: [(inv. share coefficient/capital elasticity)*(BLS relative depreciation rate)+1]*(BLS rental price for Special Ind. Machinery). The BLS estimate of the user cost for Special Industry Machinery is 0.1449283.

[2]The BLS estimate of the depreciation rate for total capital is 0.975.

Notes: These regressions also include 3-digit SIC industry dummies and state dummies, though due to confidentiality concerns, the coefficients on these dummies are not shown.

Asterisks on investment share coefficients indicate implied relative rental price is significantly different than official (BLS) rental price (assuming only source of randomness in above formula comes from the inv. share coefficient). Asterisks on other coefficients indicate statistical significance relative to 0.

*** denotes significance at the 99% level

** denotes significance at the 95% level

* denotes significance at the 90% level

**Table 8 - Regressions using pre-estimated fixed effects**

| Dependent Variable: | 1995-1997 Fixed Effect | | | 1999-2001 Fixed Effect | | | Difference in Fixed Effects (1999-2001 minus 1995-1997) | | |
|---|---|---|---|---|---|---|---|---|---|
| | Coef. Estimate | | | Coef. Estimate | | | Coef. Estimate | | |
| Investment Shares: | | | | | | | | | |
| Computers | 0.18 | (0.07) | *** | 0.24 | (0.08) | *** | 0.14 | (0.05) | ** |
| Office Equipment | 0.12 | (0.18) | | 0.01 | (0.20) | | -0.11 | (0.13) | |
| Communications and AV Equipment | 0.20 | (0.11) | * | 0.41 | (0.14) | *** | 0.22 | (0.11) | ** |
| Software | 0.49 | (0.15) | *** | 0.41 | (0.16) | *** | 0.06 | (0.11) | |
| Fabricated Metal Products | -0.09 | (0.15) | | 0.01 | (0.17) | | 0.06 | (0.12) | |
| Metalworking Machinery | 0.07 | (0.08) | | -0.01 | (0.08) | | -0.04 | (0.06) | |
| General Purpose Machinery | 0.21 | (0.10) | ** | 0.24 | (0.11) | ** | -0.11 | (0.08) | |
| Autos | 0.03 | (0.21) | | 0.13 | (0.19) | | 0.31 | (0.13) | ** |
| Trucks | 0.08 | (0.17) | | -0.08 | (0.18) | | 0.14 | (0.14) | |
| Aircraft | -0.04 | (0.15) | | -0.22 | (0.18) | | -0.13 | (0.13) | |
| Other Transportation Equipment | 0.03 | (0.15) | | -0.05 | (0.17) | | 0.22 | (0.12) | * |
| Industrial Buildings | 0.20 | (0.10) | * | 0.10 | (0.13) | | -0.01 | (0.08) | |
| Offices | 0.46 | (0.12) | *** | 0.22 | (0.13) | | -0.20 | (0.10) | ** |
| Commercial Buildings | -0.02 | (0.08) | | -0.09 | (0.09) | | 0.17 | (0.06) | *** |
| Utility Structures | 0.09 | (0.08) | | 0.13 | (0.11) | | 0.26 | (0.07) | *** |
| Other Structures | -0.01 | (0.10) | | 0.06 | (0.12) | | 0.28 | (0.08) | *** |
| Instruments | 0.14 | (0.15) | | -0.14 | (0.19) | | 0.05 | (0.14) | |
| Electrical Equipment | 0.05 | (0.10) | | -0.06 | (0.13) | | 0.10 | (0.08) | |
| Miscellaneous Equipment | 0.02 | (0.07) | | -0.02 | (0.09) | | 0.08 | (0.06) | |
| Constant | -0.11 | (0.04) | *** | -0.07 | (0.05) | | -0.07 | (0.03) | ** |
| | | | | | | | | | |
| Number of Observations | 1225 | | | 1178 | | | 844 | | |
| R-Sq | 0.1473 | | | 0.1319 | | | 0.081 | | |

Robust standard errors are shown in parentheses.

First-stage regressions – used to obtain productivity residuals – contain industry, state, size, and spike dummies

*** denotes significance at the 99% level

** denotes significance at the 95% level

* denotes significance at the 90% level

**Table 9 -- Production Function Regressions**

| | (1) 1998 | | | (2) 1999 | | | (3) 2000 | | | (4) 2001 | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Coef. Estimate | | | Coef. Estimate | | | Coef. Estimate | | | Coef. Estimate | | |
| Investment Shares: | | | | | | | | | | | | |
| Aircraft | 0.06 | (0.15) | | -0.175 | (0.21) | *** | -0.25 | (0.22) | | -0.08 | (0.22) | |
| Autos | 0.45 | (0.39) | | 0.50 | (0.47) | | 0.45 | (0.39) | | 0.52 | (0.37) | |
| Commercial Buildings | 0.04 | (0.16) | | -0.09 | (0.18) | | -0.24 | (0.17) | | -0.14 | (0.16) | |
| Communications and AV Equipment | 0.49 | (0.21) | ** | 0.84 | (0.24) | *** | 0.86 | (0.24) | *** | 0.83 | (0.29) | *** |
| Computers | 0.52 | (0.10) | *** | 0.52 | (0.12) | *** | 0.45 | (0.13) | *** | 0.47 | (0.13) | *** |
| Electrical Equipment | -0.13 | (0.16) | | -0.12 | (0.21) | | -0.08 | (0.20) | | 0.12 | (0.20) | |
| Fabricated Metal Products | 0.05 | (0.13) | | -0.06 | (0.14) | | 0.06 | (0.18) | | 0.13 | (0.17) | |
| General Purpose Machinery | 0.19 | (0.11) | | 0.12 | (0.12) | | 0.26 | (0.15) | * | 0.38 | (0.16) | ** |
| Industrial Buildings | 0.14 | (0.12) | | 0.07 | (0.13) | | 0.01 | (0.15) | | 0.17 | (0.14) | |
| Instruments | 0.16 | (0.16) | | 0.05 | (0.18) | | -0.13 | (0.20) | | -0.16 | (0.18) | |
| Metalworking Machinery | 0.07 | (0.08) | | 0.01 | (0.09) | | 0.03 | (0.10) | | -0.02 | (0.09) | |
| Miscellaneous Equipment | 0.22 | (0.12) | * | 0.12 | (0.13) | | 0.07 | (0.13) | | 0.16 | (0.12) | |
| Office Equipment | 0.16 | (0.23) | | 0.07 | (0.24) | | 0.12 | (0.27) | | 0.13 | (0.27) | |
| Offices | 0.56 | (0.17) | *** | 0.40 | (0.18) | ** | 0.54 | (0.20) | *** | 0.55 | (0.20) | *** |
| Other Structures | -0.03 | (1.68) | | 0.17 | (0.20) | | 0.05 | (0.21) | | 0.32 | (0.22) | |
| Other Transportation Equipment | 0.02 | (0.23) | | -0.28 | (0.27) | | -0.17 | (0.26) | | 0.09 | (0.26) | |
| Software | 1.08 | (0.25) | *** | 0.95 | (0.27) | *** | 0.86 | (0.23) | *** | 0.83 | (0.23) | *** |
| Trucks | 0.09 | (0.28) | | -0.15 | (0.30) | | -0.15 | (0.29) | | -0.03 | (0.28) | |
| Utility Structures | -0.02 | (0.15) | | -0.15 | (0.21) | | 0.10 | (0.20) | | 0.37 | (0.18) | ** |
| Interactions | | | | | | | | | | | | |
| High-tech * High-tech | -0.58 | (0.29) | ** | -0.74 | (0.34) | ** | -0.77 | (0.35) | ** | -0.59 | (0.33) | * |
| Low-tech * Low-tech | -0.51 | (0.31) | | -0.12 | (0.34) | | -0.44 | (0.37) | | -0.60 | (0.37) | |
| High-tech * Low-tech | 0.37 | (0.19) | * | 0.53 | (0.21) | ** | 0.37 | (0.24) | | 0.40 | (0.24) | * |
| Other Variables: | | | | | | | | | | | | |
| log(emp) | 0.54 | (0.05) | *** | 0.54 | (0.05) | *** | 0.53 | (0.04) | *** | 0.50 | (0.05) | *** |
| log(k) | 0.41 | (0.02) | *** | 0.42 | (0.02) | *** | 0.45 | (0.03) | *** | 0.44 | (0.02) | *** |
| Size Class2 | -0.03 | (0.06) | | -0.09 | (0.07) | | -0.06 | (0.07) | | -0.03 | (0.07) | |
| Size Class3 | 0.02 | (0.07) | | -0.04 | (0.08) | | -0.03 | (0.08) | | 0.02 | (0.09) | |
| Size Class4 | -0.02 | (0.10) | | -0.05 | (0.10) | | -0.05 | (0.09) | | 0.01 | (0.11) | |
| Size Class5 | 0.08 | (0.14) | | 0.06 | (0.14) | | -0.10 | (0.14) | | 0.02 | (0.11) | |
| Spike dummy | 0.07 | (0.04) | ** | 0.08 | (0.04) | ** | 0.06 | (0.04) | | 0.04 | (0.04) | |
| Constant | 0.36 | (0.18) | ** | 3.03 | (0.20) | *** | 3.24 | (0.21) | *** | 3.14 | (0.22) | *** |
| Number of Observations | 1461 | | | 1371 | | | 1277 | | | 1295 | | |
| R-Sq | 0.912 | | | 0.897 | | | 0.901 | | | 0.907 | | |

Notes: These regressions also include 3-digit SIC industry dummies and state dummies, though due to confidentiality concerns, the coefficients on these dummies are not shown. "High-tech" consists of Computers, Communications Equipment, Software, Instruments, Electrical Equipment, Metalworking Machinery, Autos, Aerospace, and Special Industry Machinery. "Low-tech" consists of Other Office Equipment, Fabricated Metal Products, Heavy Duty Trucks, Other Transportation Equipment, General Purpose Machinery, Miscellaneous Equipment, and all Structures Types.

Robust standard errors are shown in parentheses. Coefficients on Industry and State dummies not shown.

*** denotes significance at the 99% level

** denotes significance at the 95% level

* denotes significance at the 90% level

**Figure 1. Time Path of Production Function Regression Coefficients**