

# **Sunk Costs and the Depth and Probability of Technology**

## **Adoption**

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### **ABSTRACT**

I propose that sunk costs of learning and the output over which these costs are spread determine the probability and depth of technology adoption. Depth of adoption describes the extent to which firms exploit the advantages of the technology. I find that plant size but not firm size predicts CAD and CNC adoption. Learning costs are lumpy, are closely connected to technology adoption and determine both the probability and depth of adoption. Depth of adoption is considerably more plant idiosyncratic than the decision to adopt.

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## I. INTRODUCTION

Adopting a new technology involves three decisions, two of which are studied here: whether to adopt or not and the extent to which the capabilities of the new technology will be exploited – the latter labeled “depth” of adoption. The third decision regards the replacement speed of old with new technology. There are three stylized facts related to these three decisions. Large firms are more likely to adopt new technology than small firms (Rogers [1995], Thirtle and Ruttan [1987]). Having adopted new technology, large firms will learn about and utilize the new technology more than small firms (Fichman and Kemerer [1997]). However, the replacement speed of old with newly adopted technology – the intra-firm diffusion speed – is inversely related to firm size (Mansfield, 1963). Sunk costs associated with adoption can explain these results. As the output to which the technology applies increases the sunk costs are spread over a more substantial output volume that, in turn, increases the incentive to both adopt and exploit the technology. Sunk costs also imply that small firms make proportionally larger adjustments to their capital stock than large firms when adjustments are made (Doms and Dunne [1998], Bertola and Caballero [1990]). This explains the inverse relationship between firm size and replacement speed.

The objective of this paper is to test the sunk cost explanation and to distinguish it from other explanations using data on the probability and depth of adoption of Computer Aided Design (CAD) and Computer Numerically Controlled (CNC) machine tools. I focus on one sunk cost: learning how to use new technology. I study learning costs because they are more likely to be sunk than, for example, equipment costs. The main contribution is to show that sunk learning costs are important in explaining firms’ technology adoption behavior.

Depth of adoption is a relatively new construct defined as the extent to which a firm exploits an innovation’s potential technological capabilities (Cooper and Zmud [1989], Ettlíe and Reza [1992]). However, since I cannot consider all possible ways a technology may be exploited, I focused on one key feature: plants’ exploitation of the computerized data-transfer features of

CAD and CNC, respectively. It has been documented that increased use of computerized data-transfer reflects a higher sophistication of use of both CAD and CNC (Dean *et al.* [1992], Liker *et al.* [1992a, 1992b]). Depth of adoption does not measure the number of machines installed but the degree to which the technological capabilities of the installed machines are exploited.<sup>1</sup>

To test the sunk cost explanation I note that the adoption of a specific technology depends on the expected volume of output to which the costs will eventually be applied.<sup>2</sup> For CAD and CNC machine tools the cost-spreading output is based on plant size rather than the overall size of the firm. That is, sunk costs of learning imply plant-level cost-spreading scale economies for these technologies. There are other potential plant-level and firm-level scale economies such as multi-product or multi-plant operations that may also explain a positive association between plant size and adoption. I assess the relative power of sunk costs compared to alternative scale economy explanations that either center on the effects of the firm as a whole or that focus on other plant-level effects.

A Heckman two-stage selection model is used to examine the two adoption decisions. New empirical evidence hereby emerges that sheds further light on the effects of sunk costs compared to a previous paper where I collapsed the two decisions using an ordinal probit model (Åstebro, [2002]).

CAD and CNC are of general interest as examples of technologies that have wide application in the manufacturing sector. CNC and especially CAD exhibited rapid diffusion in the late 1980s. In 1983, the penetration of CAD was 4% and the penetration of CNC was 16%. By 1993, CAD had been adopted by 54% of the plants while 44% had adopted CNC. Depth of adoption is measured as the extent to which plants exploit the computerized data-transfer features of CAD and CNC once adopted. In 1993, 57% of CAD and 50% of CNC adopters had at least partial computer integration between CAD or CNC and at least one business function outside of its focal business function or with one customer or supplier. By 1993, the plants that had adopted CNC had converted 26% of all their machines into CNC, while approximately 5% were numerically controlled and the remaining 68% were conventionally controlled machines.

Clearly, the intra-firm machine replacement process was far from complete in 1993, while the level of depth of adoption had reached a reasonably advanced state for at least 50% of the adopters.

I show that learning costs associated with investments in new technology predict both the probability of adoption and the extent of use of new technology. In comparison to the probability of adoption, however, the depth of adoption is considerably less sensitive to both plant size and sunk costs. CAD and CNC adoption are equally sensitive to sunk learning costs. Post-adoption learning therefore appears more idiosyncratic to the plant than the decision to adopt. I further show that learning costs behave as nonconvex adjustment costs. Learning appears to be lumpy and occurs in short spells tightly connected with the installation of new technology. Results are consistent with Zeckhauser's [1968] model where not all expertise in a plant's old technology transfers to the new technology leading to a period of technology-specific learning.

Researchers indeed speculate that nonconvexities in the cost of capital arise from increasing returns, lumpy equipment, installation costs and disruptions associated with installations, as illustrated in this paper. Other recent empirical work on lumpy investment costs provides additional support for theoretical models with irreversible nonconvex investment costs (Doms and Dunne [1998], Cooper *et al.* [1999]). If capital investments are generally nonconvex there are potentially large macroeconomic consequences (Bertola and Caballero [1990]).

The rest of the paper contains the following sections: Predictions, Method, Measures, Results and Summary and Discussion.

## II. PREDICTIONS

If a plant (firm) faces sunk costs the plant is predicted to invest only when its capital stock is sufficiently far from optimal. Otherwise the firm prefers to delay adoption (Bertola and Caballero [1990]). When a combination of capital stock depreciation, technological change and cumulated shocks move the firm too far from its optimal level, the firm adopts. As the expected cost-spreading output increases the average sunk cost per unit of output decreases and the

expected economic return increases. Consequently, the prospect of economic gain derived from adoption increases both the depth and probability of adoption as the cost-spreading size of output increases.

H1: The size of output from a plant is positively related to the depth and probability of CAD and CNC adoption.

While the depth and probability of adoption will rise alongside the cost-spreading size, the effect is diminishing in size; there are diminishing returns to the adoption effort. Since the optimal effort marginally diminishes with increasing effort and because size drives the optimal effort, there will be diminishing effects of size on the depth and probability of adoption.

H2: The influence of plant size on CAD and CNC adoption is marginally decreasing.

The sunk costs associated with learning how to use a new technology relate primarily to the cost of collecting information about what system to purchase and what vendor to use, skills acquisition,<sup>3</sup> costs for adjusting the technology to the idiosyncrasies of operations and costs for organizational changes.<sup>4</sup> These costs represent both pre- and post-adoption learning efforts. The costs can be partly expected in advance. In particular, the costs of learning are expected to vary across industries.<sup>5</sup> With higher sunk learning costs, the total cost of adoption rises without affecting the gross returns, so the incentive to increase the depth and probability of adoption of CAD and CNC adoption subsides.

H3: The sunk cost of learning is negatively correlated with the depth and probability of CAD and CNC adoption.

The relationship between size and adoption should originate at the level of output to which the firm expects to apply the adopted innovation. Plants try to spread the costs of adoption over the largest output of parts having common enough features to be machined on one single machine (*Modern Machine Shop* [1984]). I therefore expect a CNC machine tool's use to relate directly to the production volume of a plant's major product line. This is because the output of a multi-plant firm is too varied to be physically applicable to a single CNC machine.

As in the case of CNC machines, applying CAD to a large output will economize on adoption costs. The output of a business unit, defined as the production volume for a group of products with homogeneous product-market characteristics, may be the maximum output to which a CAD system can be applied. The reason is that CAD systems are uniquely developed to optimize design within particular product classes and/or manufacturing processes.

Many other theories which seek to explain the positive size-adoption relationship apply, instead, to the overall size of the firm (*e.g.* liquidity constraints, scope economies, firm capabilities or diversification, see Mansfield [1968] and Davies [1979].) But, if the sunk cost argument applies, the effect of plant size should outweigh the effect of overall firm size on the adoption of technological innovations.

H4: When controlling for plant size, the overall size of the firm is unrelated to the depth and probability of CAD and CNC adoption.

### III. METHOD

I select general purpose technologies where learning is not trivial. The selection of technologies was also based on the idea that they should be fairly well studied in previous literature (*e.g.* Colombo and Mosconi [1995], Dunne [1994]) and they should have important economic effects. To test the hypotheses a national mail survey was administered to plant managers using an address register from Dun and Bradstreet and followed up with a telephone survey. The telephone survey targeted plant technology specialists (one for each technology) with detailed technology use questions.<sup>6</sup> The survey was conducted in 1993 and it requested information about conditions at the plant and firm in 1992 and, if applicable, conditions at the time of adoption of CAD and/or CNC. The adjusted sample population consisted of 1569 manufacturing plants representing 26 randomly selected metalworking industries. While 349 questionnaires were returned, 345 were usable, representing an adjusted overall response rate of 22%. To avoid estimation problems I deleted from the analysis six industries that each had less than ten observations. Some observations with missing data on outcome variables from the

telephone follow-up interviews were also removed, leaving a research sample of 270 observations (269 for CNC). The responses indicated that, in 1992, 56% of the responding plants used CAD, while 45% used CNC. These summary statistics correspond well with data from the U.S. Bureau of the Census [1989].

Due to lower economic returns on technology adoption and, accordingly, diminished interest in technology among smaller plants, I expected fewer responses from smaller plants. Survey responses were regressed on plant employees, firm sales and employees, industry, whether or not the firm was a single-plant firm, and three geographic descriptors: state, county and metropolitan statistical area. There were significant variations in response rates. To correct for self-selection, responses were weighted with the inverse of the response frequencies across strata. Use of this method is supported, for example, by Holt *et al.* [1980].<sup>7</sup>

#### IV. MEASURES

##### IV(i). Depth and Probability of Adoption

Depth of adoption is a relatively new construct of adoption behavior and is defined as the extent to which a firm exploits an innovation's potential capabilities (Cooper and Zmud [1989], Ettlie and Reza [1992]). However, since I cannot consider all possible ways a technology may be exploited, I focused on one key feature: the plants' exploitation of the computerized data-transfer features of CAD and CNC, respectively. It has been documented that increased use of computerized data-transfer reflects a higher sophistication of utilization of both CAD and CNC (Dean *et al.* [1992], Liker *et al.* [1992a, 1992b]).

While conducting the telephone survey, I asked a specialist on each technology in each plant which mode of data transfer best described data interchange between CAD and CNC, and eight *applicable* business functions internal to the plant as well as three functions external to the plant.<sup>8</sup> For each data interchange, the value 0 represents manual transfer, 1 represents computerized transfer but requires frequent manual intervention, and 2 represents computerized transfer that requires little manual intervention. The sum of the responses regarding the type of

data interchange (0, 1, or 2) across the 11 units represents the depth of adoption. The instrument is available on request. This instrument, and the explanatory formulation read to the respondent, are only slight modifications to that used by Dean *et al.* [1992] to measure “computer integration sophistication.” A benefit of using a standardized instrument is that it is possible to compare coefficient estimates across technologies.

The maximum realized score of plants’ depth of adoption is 12. The mean score of CAD depth of adoption is 1.71 (standard deviation 2.28), reflecting computerized data transfer with one business function, while the mean score of CNC adoption is 0.92 (standard deviation 1.24), reflecting partly computerized data transfer with one business function. 43% of CAD and 50% of CNC adopters had not yet integrated CAD or CNC with any business function, or with any customers or suppliers, suggesting a skewed distribution censored at zero. Indeed, scores of both distributions of observable values have their mode at the lower limit. Since no firm reached the upper limit, a correction for right censoring is unnecessary. The lognormal distribution function, which fits data truncated at zero, is therefore reasonable to apply to the observed responses. Moreover, 46% (55%) of the sample had not yet adopted CAD (CNC). Since this is a censored distribution with some data outside the observable range, and where the censoring is a decision variable, I employ Heckman’s [1979] two-stage model for sample selection.

#### **IV(ii). Size**

Conceptually one should use the expected plant output to which the adopted technologies will apply. As output expectations are unobservable, I instead use plant value of shipments in 1992 as a proxy (PL SIZE).<sup>9</sup> An alternative measure is the number of plant employees. Firm size (FI SIZE) was measured as total revenue or, alternately, total number of employees on the payroll in 1992. The two alternate measures are motivated by different explanations for the effect of the overall size of the firm, referring to either financial or human resources.

#### **IV(iii). Sunk Costs**

In an *ex post* survey, sunk cost measures are endogenous to the adoption decision and cannot be used directly as indicators of the *ex ante* cost of learning. I utilize the industry cross-sectional design to construct a proxy for *ex ante* costs. A plant's total sunk cost of learning follows from equation (1) as

$$(1) \quad tc_{ij} = f_{ij} \times e_{ij} + \mu_{ij}$$

where  $tc_{ij}$  is the total sunk cost for plant  $i$  in industry  $j$ ,  $f_{ij}$  is the plant's expected unit cost of learning,  $e_{ij}$  is the amount of learning (measured as depth of adoption) and  $\mu_{ij}$  is the effect of all other plant-level determinants. I compute

$$(2) \quad f_j = \frac{\sum tc_{ij}}{\sum e_{ij}} + u_j$$

where  $f_j$  represents an unobserved *ex ante* cost per unit of depth of adoption. This is an industry-wide (average) measure of sunk costs and variation is expected across industries. If the total number of observations in each industry with complete data on  $tc$  and  $e$  is large enough,  $f_j$  is no longer plant idiosyncratic. I delete industries with less than ten observations per industry to reduce the potential that  $f_j$  is unduly affected by an outlier.

I collect two measures of  $tc_{ij}$ , the cost of learning prior to adoption and the cost of learning after adoption. An account was requested of the overall effort made by the plant to decide whether to purchase the technology, to decide on the specifications of the technology, and to decide what vendor to use. I also inquired about the time spent learning to operate the innovation before reaching 90% of its technical capability. (Instruments available on request.) Respondents estimated that the investment decision effort before adoption spanned approximately fifteen months for each of the two technologies. On average, six months to a year were spent following adoption before reaching 90% of the technical capability of the CAD

system. For CNC, the average learning time was close to six months. The estimates correspond closely with those reported by Tyre and Orlikowski [1994] and Bessen [1997].

Equation (2) was used to compute  $f_j$  for the two measures. The measures were highly correlated ( $r=0.88$ ,  $p<0.001$  for CAD,  $r=0.95$ ,  $p<0.001$  for CNC) indicating good agreement. Principal components analysis was used on the standardized values and a score was computed using the loadings on the first eigenvector. This method provides a single measure of the sunk costs of adoption: SUNK COST.<sup>10</sup>

Other regressors are summarized in the Appendix. A correlation matrix of independent variables indicates that, except for correlations across various size measures, the correlations are not substantial enough to cause concern about multicollinearity (for details contact the author).

## V. RESULTS

Table I shows results from regressing the depth and probability of adoption on variables such as the natural log of plant value of output, log (PL SIZE), the natural log of overall firm sales, log (FI SIZE), sunk costs and others.<sup>11</sup> Heckman's two-stage model produces one set of coefficient estimates for the probability of adoption and one set of coefficient estimates for the depth of adoption conditional on adoption. Table I displays that PL SIZE has a significant positive effect on the probability of adoption across the two technologies, while the effect on the depth of adoption conditional on using the technology is positive but fails to be significant.

Comparisons of log-likelihoods reveal that the log specification for the effect of PL SIZE is superior to the linear specification supporting H2 of decreasing marginal returns to plant scale. Models with a quadratic term perform better than the linear specification, with an average difference in model log-likelihoods of 4.1. Twice the difference in log-likelihoods is significant at better than 1% (1 *d.f.*). In all cases the sign of the quadratic term for plant size is negative and it is sometimes significant. The log transform produces coefficients of the correct sign in all estimations and has the best model fit in all model comparisons. Models with the log transform have an average log likelihood 12.5 units better than the linear specification. Value of output fit

the data better than the number of employees, with an average difference in log-likelihoods of 7.2. (Alternative estimations suppressed.)

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Table I around here

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Table I also reports on the marginal effect of firm size on the probability and depth of adoption while controlling for plant size. *FI SIZE* is not significantly positively related to adoption after controlling for plant size supporting hypothesis H4.<sup>12</sup> The absence of any significant relationship between CAD and CNC adoption and overall firm size undermines alternative explanations for the size-adoption relationship that appeal to the influence of corporate level factors such as liquidity and firm capabilities that are positively correlated with firm size.

The influence of the overall firm on technology adoption may have more to do with learning transfer across plants owned by the firm than access to central company resources such as cash. To measure this effect I use a dummy variable for whether or not the plant belongs to a firm operating multiple plants (*MULTI*). (Details not reported to save space.) First, the coefficient for *MULTI* has the correct sign and is highly significant in determining the probability of adoption but not the depth of adoption when not controlling for plant size. That is, operating other plants seems not to affect the learning effort, but it might be affecting the likelihood of adoption in the focal plant. However, after controlling for plant size the dummy variable becomes insignificant. In addition, as the coefficient for plant size does not drop substantially when including *MULTI*, the effect of *MULTI* when analyzed in isolation seems completely determined by its positive association with plant size rather than being an independent effect. That is, firms operating multiple plants, on average, also operate larger plants than single-location plants and it is the operation of larger plants that determines technology adoption.

The marginal effect of the log of plant size on the log of depth of adoption is 3% to 4% while that of firm size is less than 1%. To indicate the plant size effect, the predicted mean depth of CAD adoption is 1.71 and it increases to 1.87 at one standard deviation above the mean log of plant size. The log of plant size therefore needs to increase by five standard deviations above the mean for the depth of CAD adoption to increase from one to two business functions with computerized integration. Similarly, the predicted mean depth of CNC adoption is 0.92, while it increases to 0.98 at one standard deviation above the mean log of plant size. These increases represent elasticities of 9.3% and 7.2%, respectively. In summary, the effect of plant size on depth of adoption is small and noisy, but measurable.

The predicted probability of CAD adoption is 0.52 at the mean of the regressors. The probability increases to 0.74 at one standard deviation above the mean log of plant size, while it decreases to 0.45 at one standard deviation above the mean log of firm size. These differences represent elasticities of +43% and -14% respectively. The impact of plant size on CAD probability of adoption is thus very large. Similarly, the predicted mean probability of CNC adoption is 0.42, while it increases to 0.65 at one standard deviation above the mean log of plant size and increases to 0.44 at one standard deviation above the mean log of firm size. These differences represent elasticities of +53% and +2% respectively. In summary, the effect of plant size on the probability of adoption is very large while the effect of firm size is either irrelevant or negative.

Table I also indicates the effect of sunk costs on the depth and probability of adoption. The coefficient has the predicted sign and is significant at conventional levels in three out of four cases, supporting H3. The effects of sunk costs are more than twice as large on the probability as on the depth of adoption. As sunk costs are standardized  $N(0,1)$ , the coefficients represent elasticities. The marginal effects are equally strong for CAD and CNC adoption.

A measurement issue to consider is if the correlation between the depth of adoption and sunk learning costs is co-determined by the inclusion of depth of adoption in the construction of SUNK COST (see equation (2)). To test for endogeneity I use an instrumental variable

formulation.<sup>13</sup> The coefficients for SUBK COST using the predicted values are compared to the original coefficient estimates of SUNK COST as described by Greene (1993, p. 619). This test for endogeneity failed (CAD:  $\chi^2=1.57$ ,  $d.f.=10$ ,  $p>.10$ ; CNC:  $\chi^2=0.22$ ,  $d.f.=10$ ,  $p>.10$ ).

The sunk cost explanation assumes that the sunk costs of learning are independent of the size of output to which they are applied. However, the unit costs as defined in equation (2) are found to be negatively correlated with plant size.<sup>14</sup> The correlation illustrates that (industry average) sunk costs are smaller in industries with larger average plant size. This indirect size effect might explain the negative relationship between sunk costs and adoption. However, an interaction term introduced between plant size and sunk costs showed not to be significant alleviating concerns for such indirect effects.

Further, there may be concerns that the measure of process ramp-up time may reflect equipment costs rather than learning costs. While this is possible it should be noted that two measures of learning costs are used, one reflecting prior and one reflecting post adoption learning efforts. Only the latter can reasonably be argued to reflect equipment costs. However, both of these are correlated with depth of adoption and are highly correlated with each other. Furthermore, the duration of the learning period has been previously assessed as unrelated to equipment costs (Tyre and Orlikowski [1994]). In all, several tests reveal a significant negative effect of the sunk costs of learning on the propensity to adopt across various model specifications.

An alternative explanation to the cross-sectional variation in depth of adoption is simply that plants adopt the technologies at different times. Suppose all firms in an industry choose the same depth of adoption but small firms (as shown) adopt later than large firms. Increasing the depth of adoption is shown to be costly and time consuming and therefore cannot take place instantaneously as it would be prohibitively costly. Then depth does not vary with size in steady state and the variation in the data simply reflects variation in adoption dates. I investigate this explanation using two measures. FIRSTYEAR is the year the plant first adopted the technology.

MINYEAR is the year the technology was first adopted in the industry. The coefficients for these measures do not exhibit robust effects, implying that there is no relationship between the time of the first investment and the level of depth of adoption in 1993. These results are reasonable given the speed of the learning process and the average adoption dates. To repeat, the average learning period to reach 90% of the technology's capability is 6 months for CNC and between 6-12 months for CAD. But the average time of first adoption is 1984 for CNC (st. dev. 4.9 years) and 1988 for CAD (st. dev. 3.4 years). So, the cross-sectional variation in depth of use in 1993 is likely to be steady-state rather than temporary differences.<sup>15</sup>

I now discuss various plant scale economies that might explain why plant size and technology adoption are related.

Classical capital replacement theory predicts that larger plants are more likely to adopt new technology because these have a larger capital stock and the capital stock needs replacing at regular intervals (Salter, [1966]). The larger the stock the larger the probability of replacement with a new technology at any point in time. Notice that the theory has no prediction on the depth of adoption. Furthermore, the explanation is only applicable to CNC adoption since CAD primarily replaces labor.

First, it can be established that plant output and the size of the capital stock are positively correlated. The simple correlation between plant shipments and the number of conventional machine tools is  $r=0.39$  ( $p<0.001$ ), and between plant shipments and the number of NC machine tools it is  $r=0.26$  ( $p<0.001$ ). In addition, Table I illustrates that the probability of adopting CNC machine tools decreases with a younger stock of conventional and NC machines after controlling for plant size. However, the coefficients for CV5Y and NC5Y are far from significant. In sum,

while the size of the capital stock is correlated with plant size, classical capital replacement theory does not explain the probability of CNC adoption.

An alternative explanation for the positive association between plant size and depth of adoption is that decision makers in small plants are more risk averse (Mansfield, 1968).<sup>16</sup> Risk aversion is measured by a hypothetical question posed to the plant manager of a choice between a guaranteed investment in government bonds and a risky investment in new technology with the same expected return. For risk aversion to explain the positive size-adoption relationship, it must be negatively correlated with plant size and negatively correlated with the depth of adoption. However, risk averse behavior in terms of choosing the guaranteed investment is not correlated with plant size ( $r=-0.03$ ,  $p>0.10$ ). And the coefficients for risk seeking and risk averse behavior in Table I are never significantly different from each other.<sup>17</sup> These results undermine risk aversion as an alternative explanation.

Another explanation centers on plants learning during the use of old technology as a driver of the relationship between size and new technology adoption. It might be that there is very little technology-specific learning and that all expertise in the plant's old technology transfers to the new technology.<sup>18</sup> Simple correlations between size and use of older technology are indeed positive ( $r= 0.06$  between CV and SIZE,  $p>0.10$ ,  $r= 0.23$  between NC and SIZE,  $p<0.001$ ) suggesting perhaps that current plant output might proxy a plant's cumulative learning (output) during previous technology adoptions. After controlling for plant size, NC machine tool use is positively and significantly related to the probability of CNC adoption while conventional machine tool use is positively and significantly related to the depth of CNC adoption suggesting inter-generational technology learning. However, there are no effects on CAD adoption and, importantly, the coefficients for plant size on CNC adoption does not change appreciatively

when excluding NC and CV. The latter result indicates that previous NC and CV use has independent effects on use of future technology generations that are not related to plant size.<sup>19</sup>

The final alternative explanation for the positive association between plant size and depth of adoption is scope economies. Larger plants may produce more products (Baldwin and Gorecki [1986]) and CAD and CNC may be more useful in such production environments (Carlsson [1989]). Indeed, the number of end items produced in plants (VARIANTS) is highly correlated with the log of plant size ( $r=0.24$ ,  $p<0.001$ ). However, coefficients for VARIANTS switch signs across estimations and are not significant, undermining this alternative explanation.

While many of the alternative plant scale economies may not individually contribute significantly they may together explain the association between plant size and adoption. This proposition is tested in a separate regression where I exclude the variables FI SIZE, CV, CV5Y, NC, NC5Y, AVERSE, SEEK and VARIANTS. The coefficients for plant size on depth of adoption remain at the same levels while the coefficient for size on the probability of CAD (CNC) adoption reduces (increases) by 20% (14%). There is therefore no robust support for the argument that various plant scale economies, except sunk cost-spreading, explain technology adoption.<sup>20</sup>

To summarize test results, then, H1, H3 and H4 are not rejected. However, H2 receives only partial support. The effect of plant size on depth of adoption is both noisy and small compared to the size of the effect on the probability of adoption. Alternative explanations find little support.

## **VI. SUMMARY AND DISCUSSION**

I found that sunk costs of learning significantly decrease the depth and probability of adoption, and that the marginal effect of sunk costs is more than twice as large on the probability

of adoption then on the depth of adoption. The effects are similar across CAD and CNC adoption.

The existence of sunk costs implies that the output to which these costs are applied will determine adoption behavior. Indeed, I found that both dimensions of CAD and CNC adoption were related to plant size. When controlling for plant size, overall firm size was not related to the adoption of CAD and CNC. The absence of an effect of overall firm size undercuts alternative explanations for the size-adoption relationship that appeal to the influence of corporate-level factors, such as liquidity and firm capabilities. Once controlling for plant size, I found few benefits for plants belonging to firms operating multiple plants. There was a log-linear relation between plant size and adoption, implying diminishing returns to scale. The results are robust to alternative explanations: plant output and sunk costs affect adoption independent of the age distribution of old machines, managers' risk attitudes and the use of older related technologies. Elasticities for plant size are between 4.6 and 7.4 times larger for the probability than for the depth of adoption.

I have shown that learning costs associated with investments in new technology exhibit behavior consistent with assumptions and predictions of nonconvex adjustment costs. Learning appears to be lumpy and occur in short spells surrounding the installation of new technology. Learning costs predict both the adoption and extent of use of new technology. Finally, results showed that post-adoption learning is more idiosyncratic than the decision to adopt. While there was considerable cross-sectional variation in depth of adoption the predictors drawn from the model were less successful at explaining this variation than they were able at explaining the probability of adoption.

Future research on the implications of cross-plant variation in depth of adoption would be useful. There are persistent cross-sectional differences in technology utilization across plants many years after the technologies were first adopted. What explains such persistent differences and what are the economic consequences? It would, for example, be interesting to see how post-adoption plant productivity varies over time both with different levels of depth of adoption as well as across plants with different levels of sunk costs and sizes.

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TABLE I. THE IMPACT OF SIZE AND SUNK COSTS ON THE PROBABILITY AND DEPTH OF CAD AND CNC ADOPTION.

Variables	CAD		CNC	
	(1)	(2)	(3)	(4)
	<b>Probability</b>	<b>Depth</b>	<b>Probability</b>	<b>Depth</b>
log(PL SIZE)	0.30*** (0.07)	0.04 (0.07)	0.28*** (0.07)	0.04 (0.04)
log(FI SIZE)	-0.04 (0.03)	0.00 (0.01)	0.01 (0.02)	-0.01 (0.01)
SUNK COST	-0.24** (0.09)	-0.09+ (0.05)	-0.22* (0.11)	-0.13* (0.06)
FIRST YEAR		-0.01 (0.02)		0.01 (0.01)
MIN YEAR	-0.02 (0.03)	0.02 (0.02)	-0.02 (0.03)	0.03+ (0.02)
CV	-0.13 (0.33)	0.09 (0.20)	0.37 (0.37)	0.38** (0.12)
CV5Y			-0.38 (0.51)	-0.23 (0.26)
NC	0.24 (0.23)	-0.04 (0.14)	0.92** (0.28)	-0.07 (0.15)
NC5Y			-0.41 (0.52)	-0.21 (0.20)
AVERSE	0.03 (0.26)	-0.06 (0.16)	-0.15 (0.30)	0.01 (0.18)
SEEK	0.31 (0.25)	0.10 (0.15)	0.08 (0.24)	-0.08 (0.14)
VARIANTS	-0.01 (0.04)	-0.04 (0.02)	0.03 (0.05)	-0.01 (0.02)
DEMAND	0.11 (0.21)	0.27* (0.12)	0.33+ (0.18)	0.19* (0.08)
GROW	4.14* (1.66)	0.04 (1.15)	1.00 (1.87)	0.50 (1.01)
OWNDES	-0.12+ (0.07)			
MODIF	0.14** (0.05)			
MAJOR	0.09 (0.06)			
BATCH			-0.09* (0.04)	
TOL			0.27*** (0.08)	
Model Wald Chi-square	38.62***		48.50***	
Log Likelihood	-235.4		-171.32	
N	270		269	

+ p < 0.10, \* p < 0.05, \*\* p < 0.01, \*\*\* p < 0.001

intercepts and correlation coefficients (rho) between probability and depth equations suppressed.

INDEPENDENT VARIABLES AND THEIR MEASURES

APPENDIX

Variable	Measure	Name	Mean	Std. Dev.	# observations imputed
Plant size	Number of plant employees; or value of shipments	PL SIZE	25	767	0
			2.5E+6	8.7E+07	0
Firm size	Number of corporate employees; or corporate revenues	FI SIZE	30	13585	2
			2.5E+6	4.9E+19	2
Multi-plant firm	= 1 if plant belongs to a multi-plant firm; else = 0	MULTI	0.31	0.46	0
Sunk costs	= sum(efforts spent on investment decision)j/ sum(depth of adoption+1)j. = sum(amount of time before reaching 90% of technical capability)j/ sum(depth of adoption+1)j.	SUNK COST1 (CAD)	3.74	2.96	0
		SUNK COST1 (CNC)	11.20	14.23	0
		SUNK COST2 (CAD)	3.10	2.39	0
		SUNK COST2 (CNC)	7.99	10.28	0
First year of adoption	= First year of adoption of technology k for plant i	FIRSTYEAR (CAD)	1988	3.44	0
		FIRSTYEAR (CNC)	1984	4.90	0
Year of first industry adoption	Year of first adoption among responding plants in industry j	MINYEAR (CAD)	1984	3.97	0
		MINYEAR (CNC)	1982	6.44	0
Age of stock of conv. machines	Proportion of conventional machine tools <5 years old	CV5Y	0.11	0.23	21
Age of stock of NC machines	Proportion of NC machine tools <5 years old	NC5Y	0.04	0.19	2
Conventional tools	= 1 if plant uses conventional machine tools; else 0	CV	0.84	0.37	29
NC tools	= 1 if plant uses NC machine tools; else 0	NC	0.20	0.40	11
Risk perception	= 1 if respondent chose to invest in government bonds; else = 0 = 1 if respondent chose to invest in risky manufacturing technology; else = 0	AVERSE	0.28	0.45	13
		SEEK	0.46	0.50	13
Multiproduct mfg	Likert-type scale =1 if 0-4 end items, =9 if >1,000 end items produced	VARIANTS	5.92	2.59	39
Industry demand	4-digit SIC industry value of shipments in 1992 (millions)	DEMAND	6379	8283	0
Demand growth	Linear regression coefficient for growth in price-adjusted 4-digit SIC value of shipments between 1971-91	GROW	0.05	0.19	0
designed in-house	Likert-type scale =1 if 100% own design, =5 if 0% own design	OWNDES	2.61	1.53	5
Number of design modifications	Likert-type scale =1 if none, =8 if >50 in the past year	MODIF	4.43	2.36	38
Batch size	Likert-type scale =1 if one piece, =9 if 10,000 or more pieces	BATCH	5.16	2.60	38
Plant specialization	Likert-type scale =1 if less than 30%, =7 if between 96% and 100%	MAJOR	5.47	1.68	16
Machining tolerance	Likert-type scale =1 if +/- 0.010 inch per inch or greater, =6 if +/- 0.00003 inch per inch, or tighter	TOL	2.36	1.32	22

Note: Median reported for PL SIZE and FI SIZE, i = plant index, j = industry index.

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<sup>1</sup> The number (or proportion) of old machines replaced by new measures intra-firm diffusion (*e.g.* Mansfield [1963], Antonelli [1985], Åstebro [1995]). Depth of adoption is, however, related to cumulative learning as documented in the “learning curve” literature (*e.g.* Thompson [2001]).

<sup>2</sup> Another implication of sunk learning costs is that productivity growth may at first fall and then later rise after adopting a new technology. This implication is not examined in this paper. For an analysis of this issue see Huggett and Ospina [2001].

<sup>3</sup> These skills include how to use a computer; operating system commands; specific commands and functioning of the software and hardware (Primrose *et al.*, 1986); troubleshooting, programming and simulation (Majchrzak [1986], [1988], Liker *et al.* [1992a, 1992b]).

<sup>4</sup> For example, NC programming used to be the task of production (industrial) engineers. But with the advent of on-line machine programming (the program for the next batch is developed on the machine while the machine is operating on the current batch), the programming responsibility has shifted to the machine operator, who typically has less formal education.

<sup>5</sup> There are reasons to expect that learning costs vary systematically across industries. For example, solid modeling CAD packages, which are used to portray three-dimensional forms, are more complicated and more costly to learn than simpler 2-D drafting systems. But solid modeling is only necessary used when designing complex products (*e.g.* a car fender or a prismatically shaped product). Two-dimensional products (*e.g.*, stamped parts) are easier to design and the necessary CAD tools less difficult to learn. As complexity and other product features vary across industries so will the costs of learning to use the technologies. The same argument holds for CNC learning costs.

<sup>6</sup> For details on survey design see Åstebro [2002].

<sup>7</sup> Missing data for regressors were imputed using regression. See Table I for number of observations imputed. I constructed a dummy variable whenever an observation was imputed and included that in regressions. None of these dummy variables were important or significant.

<sup>8</sup> Eight business functions were listed for each technology: marketing and sales; process planning; production scheduling; manufacturing process control; quality control and inspection; inventory control; accounting and budgeting; purchasing; and, finally, product design (product design was not applicable for CAD and manufacturing process control was not applicable for CNC). The three units external to the plant were other units of the corporation, customers, and suppliers.

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The telephone interview also contained questions regarding what type of technology was used and the date of adoption. Since data on use of technology was also requested in the mail questionnaire, inconsistencies in data reporting could be probed and resolved. Data reporting accuracy on technology use were also randomly checked by eliciting responses on the same technologies across specialists. Of 195 users of CAD already identified by their mail survey response, 160 plants (82%) responded to the telephone query. Of 157 users of CNC, 138 plants (88%) responded.

<sup>9</sup> I collected measures of both plant and business unit output. However, plant and business unit size are very similar as most business lines consisted of single plants. I therefore dropped analysis of business unit size.

<sup>10</sup> An original hypothesis was that the pre-adoption costs would be more predictive of the probability of adoption and the post-adoption learning costs would be more predictive of the depth of adoption. However, these results did not come out in the empirical analysis. Separate regressions produced very similar coefficient estimates across the two measures. I therefore collapsed the two measures into one.

<sup>11</sup> Presentation of intercepts and correlation coefficients ( $\rho$ ) are suppressed. Regressions with industry dummies produced qualitatively similar results. To identify the selection equation in the Heckman-model, I include OWNDES, MODIF, MAJOR, BATCH and TOL. Tests for whether the errors of the probability of adoption and depth conditional on adoption are correlated fail (Wald test for  $\rho=0$  are 0.13 and 1.33,  $p > 0.10$ .) The results imply that the probability of adoption and depth of adoption are not jointly determined by some unobserved variables.

<sup>12</sup> Firm size is a significant positive predictor when excluding plant size.

<sup>13</sup> As instruments for plant-level sunk costs I used all variables reported in Table I and, in addition, firm size, whether the plant belonged to a multi-plant firm, the total number of conventional and NC machine tools, and several additional production technology descriptors. The  $R^2$  of the I.V. model was 0.24 for CAD and 0.25 for CNC representing reasonable identification.

<sup>14</sup> CAD pre-adoption cost and size:  $r=-0.10$ ,  $p>0.10$ ; CAD post-adoption cost and size:  $r=-0.15$ ,  $p<0.05$ ; CNC pre-adoption cost and size:  $r=-0.16$ ,  $p<0.01$ ; CNC post-adoption cost and size:  $r=-0.12$ ,  $p<0.10$ .

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<sup>15</sup> The depth of CNC adoption is significantly and positively related to the year of first industry adoption, indicating that delayed industry-wide adoption actually increases plant-level depth of adoption. The result may be due to a catch-up effect. Independently conducted interviews with plant managers revealed that delayed industry-wide adoption is partly a function of supply-side restrictions. For example, CNC machine tools for coil winding were not available until the mid-1980s.

<sup>16</sup> As the size of a plant decreases, a risk-averse decision-maker may be less willing to commit a given capital investment since the investment will become more substantial in comparison to total revenue. As the risk of failing increases with greater variance (risk) while expected returns remain constant, the downside loss would preoccupy a risk-averse decision-maker. A risk-averse decision-maker might also curtail the initial size of the investment.

<sup>17</sup> The excluded category in Table I contains those who choose a risk neutral option so the coefficient for AVERSE is expected to be negative and that for SEEK is expected to be positive. The results are weaker than those obtained in Åstebro [2002], who analyzed the effects of these measures on an ordinal probit of adoption. A potential explanation for the difference in results between the two studies is that there is not enough power in the data to separate between effects on depth and effects on the probability of adoption. I investigated this claim by constraining the effects of AVERSE and SEEK to be zero on depth of adoption in a separate regression. This produced similar results to those reported in Table I.

<sup>18</sup> I can probe this learning argument directly for CNC adoption, since NC and conventional machines are technologically related to CNC machines. The technological similarities between conventional and NC machines on the one hand, and CAD on the other, are less obvious and therefore I do not expect strong relationships there.

<sup>19</sup> In a separate regression where I constrained the effect of CV and NC use on depth of CNC adoption to be zero, there were only miniscule changes in the coefficients for CV and NC on the probability of CNC adoption. These results are different than those in Åstebro (2002), where larger coefficients were observed. Further research seems necessary to disentangle the effects of using older technology on the adoption of new and related technology.

<sup>20</sup> A close association between plant and technology adoption may also reflect plant capabilities reflected by proxy measures such as R&D expenditures. However, Jensen (1988) refutes this argument on theoretical grounds and previous empirical work finds little support for it.