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Adoption of Advanced Manufacturing Technology and Firm Performance in the Netherlands

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Adoption of Advanced Manufacturing Technology and Firm Performance in the Netherlands

Eric Bartelsman*, George van Leeuwen**, and Henry Nieuwenhuijsen***

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Abstract

This paper presents characteristics of firms which employ advanced manufacturing technology (AMT), explores the pattern of adoption of such technology, and traces the effects of adoption on the evolution of employment and productivity. The study uses linked firm-level data on production, factor inputs and on advanced manufacturing technology. It is found that the percentage of firms which employ advanced technology increases with higher labor productivity, higher export-sales ratios, and especially larger firm size. Corrected for interactions, however, only initial size and the capital-labor ratio in 1985 aid in predicting adoption of AMT. Conditional on adoption of AMT it is seen that intensity of advanced technology inputs decrease with firm size and with labor productivity. Finally, firms which employed AMT in 1992 show higher average growth rates of employment and of the capital-labor ratio between 1985 and 1991.

1 Introduction

This paper presents an initial exploration into the characteristics of firms which use advanced manufacturing technology, the factors which contribute to adoption of this technology, and the effect of technology usage on firm performance and employment. The paper contributes to the recent evidence from many countries on these relations in industrial firms or plants. An early study which provided a comprehensive picture of the adoption of advanced technology, not dependent on case studies or aggregated data, was by Dunne (1991), who linked data on US manufacturing

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firms with a survey of manufacturing technology. Since then, similar studies have been undertaken for Canada by Baldwin and Johnson (1994), for Israel by Regev (1995), for France by Entorf and Kramarz (1995), for Italy by Vivarelli et al. (1995), and for Denmark by Nyholm (1995), among others.

Some of the findings from these studies are very similar to ours: Penetration rates of advanced technology have been seen to increase with firm (or plant) size, with labor productivity, and with export share. Further, usage of advanced manufacturing technology is seen to be correlated with high labor productivity. Most of these studies show a positive correlation between usage of advanced technology and higher wages. In the Netherlands data, this relationship is not monotonic, but hump shaped. More disparate across countries are the effects of advanced technology usage on employment growth. In Italy, Norway, and Denmark, the results point towards employment declines, while for France, UK, and US, employment growth is boosted by advanced technology usage. For the Netherlands, the data require more careful interpretation. Total employment for the firms which use AMT declines between 1985 and 1991, while it increases for the firms which do not. However, when the largest five firms are excluded, employment grows much more rapidly for AMT users than non-users. Further, the average growth rate of employment for AMT using firms is higher than for non-users, and increases with the importance of AMT for production. Not well explored in studies from other countries is the relationship between capital and AMT usage. Using measured real gross capital stock for firms in the Netherlands, our study finds that firms with a high capital-labor ratio in 1985 were more likely to have adopted AMT by 1992, and that growth in the capital-labor ratio is much higher for AMT using firms than for non-users.

A dimension of the links between AMT usage and firm dynamics highlighted in this paper is the role of shifts in technology and market demand. The usage of AMT is seen to be correlated with high growth of labor productivity. This could lead to declining employment, unless the firm's output grows rapidly enough to offset the reduced demand for employees per unit of output. This growth can occur through combinations of changing market share and changes in the size of the overall market. These interactions are studied using a framework developed by Baily et al. (1995) and applied to the Netherlands by Bartelsman et al. (1995), where firms are split into groups of successful and unsuccessful **upsizers** and downsizers. It is found that AMT users are disproportionately represented among the successful upsizers.

Another feature of this study is that three concepts of AMT use are employed. The first is an indicator variable which shows whether or not a firm uses any advanced equipment. Next is a subjective measure of the impact of equipment failure on a firm's production. Last is an AMT intensity measure which is related to the share of advanced equipment in productive inputs. The intensity variable could be constructed because of the availability of firm level capital stock measures, and counts of various types of advanced equipment, such as CNCs or mini computers.

Most other studies of manufacturing technology rely on a variable of the first type and cannot distinguish between firms on the basis of importance or intensity of the advanced equipment.

The organization of the paper is as follows: Section 2 describes the data used in the study, and closes with a description of the characteristics of firms using AMT, section 3 describes how the adoption decision is modelled and which variables are seen to be related to the adoption decision, section 4 describes the evolution of employment and productivity for AMT using firms, and section 5 closes with a summary and conclusions.

2 Data Description and Summary Statistics

The data used in this study derive from linked surveys of firms in the Netherlands manufacturing sector. The main sources of data are the Production Statistics (PS) of 1985 and 1991.¹ These data are linked with information from the 1992 Survey of Advanced Manufacturing Technology (AMT), and data from the 1982-1993 Surveys of Capital Stocks. Summary statistics of the data are given below, followed by a description of the methodology for creating capitals stock measures for all firms in the PS survey, and for creation of a technology intensity measure based on information in the AMT survey.

The PS surveys contain information on shipments, employment, materials and energy usage, inventory levels, exports, and capital consumption allowance. About 80 percent of the firms with more than 20 employees in the 1985 PS have been linked to the 1991 PS, based on firm code, name, industry and location. Real firm output has been computed as shipments plus inventory changes deflated by S-digit SIC prices with a 1985 baseyear. Materials usage is also deflated at the 3-digit level.²

The rows of table 1 provide summary statistics of the key variables, and the columns describe the **datasets** from which they are derived. The 14306 firms in the 1991 PS employed 863 thousand workers, while the 9063 firms in the 1985 PS employed 787 thousand workers.³ The linked PS85-PS91 panel-the middle column-contained 6121 firms which were in existence in both 1985 and 1991. At these firms, output grew 2-3/4 percent per year, employment increased 1 percent per year, and labor productivity increased 1-3/4 percent per year. The panel with which most of the analysis is conducted, the linked PS85-PS91-AMT92 panel (hereafter referred to as the panel), contains 1435 firms which were in existence in both 1985 and 1991 and which responded to the 1992

¹Surveys from 1978 through 1992 are available, but have not yet been linked and documented.

²In principle, firm level deflators can be created for output and materials input. This is possible because the sample frame for the producer price index statistics is derived from the firm-x-product make-table. If a firm's output of a specific product has a high coverage ratio of total production of that product, than that firm is included in the price index sample. To create a firm specific deflator, changes over time in the measured price are averaged (weighted, with product vector) with average prices for the other (secondary) products which the firm produces.

³Growth rates from 1985 to 1991 are not given in the 'All Firms' column because the 1991 PS included firms with less than 10 employees while the 1985 survey did not.

AMT survey. Output growth is about the same as for the the **PS85-PS91** panel, but employment declines, resulting in labor productivity growth of about 3 percent per year. Prom table 2 it is seen that the panel is overrepresented by larger firms, and by firms in metals and electrical equipment, reflecting the design for the AMT survey and the sample selection from survival caused by linking the 1985 and 1991 PS surveys.

The last two columns of table 1 show key variables for firms which do not and do use AMT, respectively. Even though productivity growth is higher for firms using AMT, both output and employment growth are lower. This surprising result is endemic in aggregate statistics derived from a skewed size distribution of firms, such as in the Netherlands. The largest five firms comprised more than 10 percent of output and **12-1/2** percent of employment in all manufacturing in 1985. Table A.1, in the Appendix, shows the summary statistics excluding the five **firms**.⁴ Excluding these five firms, employment growth in the panel is about **1-3/4** percent per year. Because each of the five firms use AMT, the figures in the last column are especially sensitive to the problem. Employment growth for AMT users excluding the five largest firms is 2 percent per year, compared with 0.9 percent for non-AMT users.

Rather striking are the results for changes in the capital-labor ratio. The construction of these figures, which are rather unique among studies of this type, will be described below. The last row of the table shows annual changes in the capital-labor ratio of nearly 6 percent per year. Further, the growth rate is much higher for AMT using firms than for the others, although this may partly reflect size and industry effects.

2.1 Capital Stocks

The lack of firm or plant specific capital stocks has often been a serious problem with micro-level productivity studies. In our study, we have been able to create firm level (gross) capital stocks by combining measures for the larger firms from the survey of capital stocks with information on capital consumption allowances (CCA) for all firms from the production **statistics**.⁵

The survey of capital stocks measures historical and current value of gross capital stock by vintage and type. The survey is conducted annually, starting in 1982, and covers firms with more than 100 employees. Each year firms within a selected group of industries are surveyed, with all industries being covered within a five year period. The largest firms have a high probability of being resampled in a subsequent five-year period; so far, about 250 firms have been sampled more than **once**.⁶

⁴Not all of the five firms reduced their employment over this period, but for disclosure reasons, we exclude the top five.

⁵Regev (1995) makes use of a related methodology to combine data from a capital stock survey to firm specific information on depreciation in order to create capital stocks.

⁶In a future study we plan to use the firms which have been sampled more than once to estimate a stochastic mean-service life function with business cycle specific effects.

Table 1: Summary Statistics, PS85, PS91, AMT92

		All Firmsf PS85–PS91		PS85–PS91–AMT92		
				A l l	AMT=0	AMT=1
Firms	1991	14306	6121	1435	614	821
Firms	1985	9063				
Output ^a	1991	317922	275884	98049	15748	82301
output	1985	266662	234160	83210	13080	70130
Output Growth			2.77	2.77	3.14	2.70
V.Add ^a	1991	88779	60829	23429	3123	20305
V.Add	1985	68877	61125	24398	3309	21089
V.Add Growth			-0.08	-0.67	-0.96	-0.63
Employment ^f	1991	863624	717865	264334	43439	220895
Employment	1985	787400	678005	268063	41219	226844
Empl. Growth			0.96	-0.23	0.88	-0.44
Wage ^c	1991	61	6 2	63	56	65
Wage	1985	57	58	59	52	60
Wage Growth			1.19	1.20	1.04	1.25
Productivity ^d	1991	368	384	371	363	373
Productivity	1985	339	345	310	317	309
Prod. Growth			1.80	3.01	2.24	3.16
TFP Growth			-1.76	-1.59	-2.80	-1.27
K-L Ratio ^e	1991	361	327	352	174	387
K-L Ratio	1985	238	231	244	150	261
K-L Growth			5.96	6.30	2.51	6.78

^a Thousands, ~~1985~~ Guilders
^b Number of Employees
^c Thousands, ~~1985~~ Guilders
^d Output per employee, thousands, ~~1985~~ Guilders
^e Gross capital stock per employee, thousands, ~~1985~~ Guilders
^f The 1991 PS includes firms with less than 20 employees

Table 2: Panel Coverage, PS85-PS91-AMT92

	Firms		Production ^a			Employment ^b		
	PS 91	Panel	PS 91	Panel	Pct.	PS 91	Panel	Pct.
1-19	6640	144	11418	539	4.7	52	2	3.8
20-49	3450	393	24546	2867	11.7	108	13	11.6
50-99	1673	346	29452	5967	20.3	115	24	21.1
100-199	872	317	37950	13638	35.9	121	44	36.3
200-499	483	169	54629	16295	29.8	144	51	35.7
500 +	199	66	159667	58743	36.8	323	130	40.3
Food and Beverage	1917	197	86705	21507	24.8	147	36	24.3
Other nondurables	3609	261	21335	5339	25.0	107	25	23.8
Paper, Publishing	1911	173	25286	5942	23.5	99	21	20.9
Chemicals and Allied	1159	156	90913	24819	27.3	135	33	24.7
Metals and Products	2374	247	27383	10178	37.2	114	41	36.2
Machines	1519	228	17499	4962	28.4	86	25	29.1
Electrical Eqpt.	636	65	30155	19361	64.2	105	61	58.2
Transport Eqpt.	802	83	17177	5583	32.5	61	19	31.2
Miscellaneous	379	25	1470	358	24.4	9	3	27.8

^a Thousands, 1985 Guilders
^b Thousands

The capital stock variable is thus either measured directly, by aggregating over vintage and type for the firms in the capital stock survey, or by linking this information to the production statistics to create an implied stock for the firms where stocks are not directly observed. The production statistics include a question concerning capital consumption allowances. The CCA is related to the size of the capital stock, but also reflects tax laws and state of the business cycle. The strict proportionality between the CCA and gross capital stock is thus broken by cross sectional variation in tax treatment (owing to differences in type and vintage of the capital asset) and state of the market. The CCA for those firms which have a measured gross capital stock can be used to derive the implicit ‘depreciation’ as the ratio between the CCA and the capital stock. By averaging the implied depreciation rate for firms within an industry for both 1985 and 1991, we can compute the real gross capital stock for those firms where the stock is not observed. Implicit in the methodology is the assumption that the vintage-type distribution of capital assets are the same for all firms within a specific industry in a specific year.

The actual calculation of capital stocks for each firm is complicated by three factors. First, we match firm observations from the capital stock survey for the year of the production survey as well as the two previous and subsequent years. Thus, for the 1991 PS we find firm matches in the capital stock surveys from 1989 through 1993. We assume that the process of averaging the implied depreciation rate corrects for this problem. Second, we try to average the depreciation rates at the 4-digit industry level, but require at least 5 observations. We aggregate up the industry hierarchy to meet this condition. For example, some 2-digit industry have less than 5 firms with measured

Table 3: CD Production Function: Elasticity Estimates

Factor	PS85 log level	PS91 log level	PS85-91 first diff.	P S - A M T first diff.
Capital	0.068 (.003)	0.078 (.003)	0.045 (.003)	0.041 (.006)
Labor	.257 (.004)	.311 (.004)	.246 (.006)	.207 (.013)
Materials	.681 (.003)	.625 (.003)	.650 (.005)	.675 (.010)
R ²	.99	.99	.90	.91
# obs.	8616	13000	6121	1435
memo: avg. capital share	.09	.09		

capital stocks so that the manufacturing average depreciation rate is used. Third, for firms which are measured in one year, but not in the other, we derive the capital stock change from the change in the capital calculated in both years by using the CCA and implied depreciation.

The implied depreciation rates of capital computed using this methodology have a cross sectional distribution which falls in an economically reasonable range, between 4 and 15 percent.⁷ Further, the capital output elasticity computed using a Cobb-Douglas production function on (log) first differenced firm-level panel data of gross output, capital, labor, and materials gives a highly significant coefficient of the appropriate magnitude. Table 3 shows the estimated output elasticities for the log-level specification from the PS85 and PS91 cross sections, and elasticities for log first difference specification from the linked PS85-PS91 and the linked PS-AMT panels. The form of the estimated equation is given below:

$$q_i = \alpha_k k_i + \alpha_l l_i + \alpha_m m_i + \varepsilon_i$$

where q measure real gross output, k real gross capital, l number of employees, and m is real materials input. As seen, these elasticities seem reasonable, although for the within estimates (columns 4 and 5), they are smaller than the measured revenue shares.⁸

Table 4 shows the annual average growth rate from 1985 to 1991 of the real gross capital stock by 2-digit industry group. In the second column of the table are the published growth rates. As seen, the growth rates for the firms in our sample are much higher. The differences could be

⁷For the dairy industry, depreciation rates calculated in this manner were near 50 percent. Further investigation revealed that the capital stock survey did not include capital owned by cooperatives to which the firms belonged, but that the CCA reflected full value of the capital.

⁸These results are however better than most within estimates using micro data. The framework used by Olley and Pakes (1992) is able to get good results using an unbalanced panel with explicit recognition of sample selection bias. Even in that study, however, the production function is estimated in (log) levels.

Table 4: Capital Stock Growth 1985-1991

	Official	PS85-PS91	PS85-PS91-CC92		
			All	AMT=0	AMT=1
Total Industry	1.58	6.74	5.87	3.35	6.12
Food and Beverage	.69	6.10	4.72	6.84	4.56
Other nondurables	1.95	8.56	8.73	4.52	9.27
Paper, Publishing	2.64	10.41	11.95	9.56	12.49
Chemicals and Allied	1.73	8.42	10.84	-3.31	12.51
Metals and Products	1.52	5.43	4.44	9.41	4.26
Machines	1.98	6.12	4.29	7.21	3.67
Electrical Eqpt.	1.16	1.32	-0.40	9.65	-0.82
Transport Eqpt.	1.61	2.53	3.43	-3.17	5.65
Miscellaneous	.57	6.19	10.33	3.55	12.16

a Gross capital stock, annual average growth

attributed to the sample selection (larger, more succesful firms), and to differences in methodology. The published figures were computed by imputing stocks for all unmeasured firms based on an extrapolation of capital labor ratios. This method likely inflated the total stocks in both years, reducing the growth rates.

2.2 Survey of Advanced Manufacturing Technology

The AMT survey was conducted in 1992 among large firms. Within manufacturing, about 2200 firms were linked to the 1991 PS, and about 1500 firms were found in the linked PS85-PS91 panel. The survey asked firms about their use of computer aided manufacturing, design, and planning. However, the inquiries of this paper are limited to information on computer aided manufacturing equipment because it is this technology which is most thought to lead to labor productivity improvements through a streamlining of production processes with associated job losses.

The survey asks respondents to indicate whether they used any of a list of computer aided manufacturing process technologies. These technologies include CNC (computer numerical control), DNC (distributed numerical control), Pick and Place systems, robots, programmable logic controllers, and PC's, mini's, and mainframe computers. For most of these technologies, firms were asked to indicate how many pieces of this type were in operation.

The results on adoption of AMT are subject to some caveats. First, the date of adoption is not actually observed, only the fact that firms use AMT in 1992. It is implicitly assumed that the firms did not yet use these technologies in 1985 and that it is reasonable to model the the adoption decision using information from that year in order to predict AMT usage in 1992.⁹

Second, the use of AMT is a binary choice variable and does not provide information about

⁹Once the next AMT survey becomes available, this assumption can be relaxed.

Table 5: Aggregation weights for AMT index

Type	Coefficient
(C)NC equipment	500
DNC equipment	3000
Transport system	13000
PC'S	6000
Workstations	25000
Mainframe	10000
PLCs (max 200 i/o's)	25000
PLCs (> 200 i/o's)	85000
Distr. Control System	150000

the extent of usage. Thus, if firm size were a good predictor of adoption, which it appears to be, this may reflect nothing more than the fact that large firms are likely to have at least one PC, for example. This problem plagues most other studies of AMT surveys, although Dunne (1991) created an index of intensity by summing the positive responses to binary questions on usage of different technology. Using the Netherlands data, two possibilities exist to correct for the problem. First, it is possible to construct an index of technology intensity which reflects the proportion of factor inputs belonging to the class of AMT equipment. The AMT survey contains counts of different types of equipment, such as CNCs or robots. In order to create an index of technology usage, some weights are needed to aggregate the quantity responses. A simple approach is to regress these quantities on the firms real capital stock and use the estimated coefficients as weights.¹⁰ The table below gives the weights (interpretable as prices in 1985 guilders) used to aggregate the technologies.

Another possibility is to use the answer to a subjective survey question: "What would be the impact on your production if the aboved mentioned equipment failed?" The AMT usage index mentioned above is correlated with the subjective survey response, as shown in the table below. In the next sections we will explore the relation between 1985 firm characteristics and the AMT usage index and the subjective importance of AMT, and show how firm dynamics, especially employment growth, relate to these AMT measures.

2.3 Who Uses Advanced Manufacturing Technology?

In the publication of results from the survey of manufacturing technology, Statistics Netherlands (1992) showed that adoption of AMT technology increases by firm size class. Further, the publication reported on variation of adoption by industrial classification, along with information

¹⁰The two size categories of programmable logic controllers only allowed a binary response, and were included as dummies in the regression. The coefficients were restricted to be no-negative using constrained maximum likelihood procedure.

Table 6: Production Impact of Failure of AMT and AMT Intensity

Impact Category	AMT Intensity (avg.)
Nihil	.84
Marginal	.92
Substantial	1.08
(Virtually) Complete	1.47

on type of technology and investments and planned investments in 1992 and 1994. However, no further firm characteristics were included as queries in the survey. By linking the firm level statistics with data from the 1991 survey of manufactures, we are able to describe more completely the characteristics of the plants which employed advanced technology in 1992. In chart 1 we present penetration of technology (as percent of number of firms) by size, wage labor productivity, and export share.

As seen, the percentage of firms employing such technology increases rapidly with firms size, to more than 92 percent for firms with more than 500 employees. (Size is measured by total employment and disaggregated by size class definitions of Statistics Netherlands.) This result, however, highlights the shortcoming of this approach. Whether or not a firm uses AMT is not an indicator of intensity of use of such equipment, so that even if the pattern of (unobserved) intensity across size class were uniform, one would still expect to see rising adoption probabilities with firm size. In the next section the evidence is given on the variables which are correlated with AMT-intensity, conditional on having adopted some technology.

The percentage of firms using AMT increases in the low wage quintiles but flattens out and decreases in the highest quintile. (Wages are measured by total 1991 payroll divided by employment-in thousands per worker, deflated by CPI, 1985=100—and split by quintiles of workers.) As seen, the cross-sectional distribution of average firm wages is rather narrow in the Netherlands, with the median worker in the lowest quintile earning about 55 percent of the median worker in the top quintile.

The ratio of exports to sales of AMT-using firms is also higher than those without, and penetration is seen to increase with this ratio. (The export ratio shows nominal exports as a percentage of sales, split by quintile of sales.) Lastly, penetration of AMT increases with output per employee (measured in thousands of 1985 Guilders of gross production per worker, split by quintiles of

employees).

However, consistent with results in other countries, we find significant interactions between these characteristics. For example, our sample shows AMT adoption increasing with size, as well as a considerable size-wage premium. As such, the bivariate plots show little about the role of the characteristics in adoption of advanced technology. In the next section the discrete adoption choice is modelled as a function of the characteristics and their interactions.

3 Adoption of AMT and 1985 Firm Characteristics

Our data do not distinguish the date at which AMT has been adopted. It seems safe to assume that firms that employed AMT in 1992 most likely had it in 1991. It is further assumed that these technologies had not been adopted by 1985, so that one can consider the 1985 firms characteristics as exogenous to the adoption decision.¹¹ Table 7 shows the results of a probit regression explaining the adoption probability of AMT using size and industry dummies, as well as 1985 observations on wages, labor productivity, TFP, capital labor ratio, export share of output, and interactions of wages with size. The probit regression is represented by:

$$\text{Prob}(AMT_i = 1) = 1 - \Phi(-X_i\beta),$$

where Φ is the cdf of the standard normal, β is a vector of parameters to be estimated and X is the matrix of independent variables. This is derived from the equation:

$$y^* = X\beta + u,$$

where y^* are unobserved responses with $y = 1$ if $y^* > 0$, $y = 0$, otherwise, and u are normally distributed.

In the first column-without size and industry dummies-it is seen that the capital-labor ratio, export ratio, wage, and wage squared have a significant effect. When the dummies are included—the second column-the wage and export ratio effects decline as does their significance. The size dummies are highly significant and show the adoption probability rising sharply with size. By industry, higher adoption probabilities are found in the food and beverage industry (the omitted category) and in the machinery industry. When wages are interacted with size, significant positive wages effects occur for the smallest firms, but a negative effect for the largest ones.

¹¹At a later date an attempt will be made to test for robustness of our results to this assumption by analyzing adoption probabilities conditional on 1980 firm characteristics. Unfortunately, our sample will become smaller and will contain larger and older firms, and will no longer contain a capital stock variable. Note also that because AMT penetration is only available at one point in time, it is not feasible to model a technology diffusion pattern, but only whether firms do or do not employ AMT.

Table 7: AMT Adoption Model, PROBIT

	Model I			Model II			Model III		
	β	Std.	Err.	β	Std.	Err.	β	Std.	Err.
Constant	-2.042		.408	-1.728		.432	-1.193		.542
Wage	.068		.015	.048		.016	.032		.018
Wage ²	-.001		.000	-.001		.000	-.001		.000
K-L ratio	.001		.000	.001		.000	.001		.000
Labor Prod.	.000		.000	-.000		.000	-.000		.000
Exp/Sales	.007		.001	.003		.001	.003		.001
Size Dummies									
20-49				.277		.1204	-.591		.493
50-99				.729		.1279	.633		.528
100-199				1.074		.1395	.944		.590
200-499				1.165		.1618	.927		.713
500 +				1.928		.2754	3.144		1.258
Size Dummies interacted with Wage									
20-49							.018		.009
50-99							.003		.010
100-199							.004		.013
200-499							.006		.015
500 +							-.017		.019
Industry Dummies									
Other nondurables				-.091		.130	-.086		.123
Paper, Publishing				-.189		.145	-.202		.155
Chemicals and Allied				-.097		.161	-.086		.143
Metals and Products				-.108		.135	-.095		.136
Machines				.065		.130	.077		.128
Electrical Eqpt.				-.432		.196	-.423		.192
Transport Eqpt.				-.967		.183	-.972		.183
Miscellaneous				-1.030		.312	-1.048		.308
χ^2									
DE		1502	1559		1518		1500		
					1489		1484		
P	.148			.293			.380		

Table 8: AMT Usage Index

	β	r-stat
Constant	.17	.2
Wage	.00	.0
Wage ²	.00	.1
K-L ratio	.28	3.9
Labor Prod.	-.09	5.1
Exp/Sales	.25	1.2
Size Dummies		
20-49	-.99	-3.5
50-99	-1.43	-4.9
100-199	-1.97	-6.2
200-499	-2.37	-6.5
500 +	-2.84	-6.1
$\lambda(X'\alpha_1)$	.00	.4
R ²	.12	
Num. Obs.	820	
Industry dummies included.		

Figure 2 shows the adoption probability by wage as a result of a probit regression with only wage and wage squared as explanatory variables (the dotted line) and the results from a probit with size dummies, industry dummies, the capital-labor ratio and the export share, along with wage and wage squared as explanatory variables (the solid line). As can be seen, the wage effect peaks earlier once the other covariates are taken into account. The following equation shows how the probability is evaluated.

$$\phi(\bar{w}) = \bar{c} + \int_0^{\bar{w}} (W\beta_w + W^2\beta_{w^2})dw$$

where $\bar{c} = 1/N * \sum_i \tilde{X}_i\tilde{\beta}$, $\mathbf{W}$ is the wage, $\tilde{X}$ are the other explanatory variables. In other words, the contribution of wage and wage squared are added to an intercept which is the sum of the other effects measured in the **probit** equation (including constant term) evaluated at their means.

The **Probit** regression shows how certain characteristics influence the probability that a firm uses AMT. Conditional on having adopted some piece of AMT equipment, the role of the firm's characteristics on the 1992 AMT intensity is explored. The intensity index was regressed on size and industry dummies, and on wages, wage squared, labor productivity, the export ratio and the capital-labor ratio. The results are shown in table 8. In contrast to the binary choice adoption regression, intensity of AMT usage declines with size and labor productivity and increases with the capital-labor ratio. Further, wage effects are no longer significant.

The role of firm size for adoption and usage of AMT seem at odds with each other. For the

adoption model, the threshold for a large firm in purchasing one piece of AMT equipment is clearly very small, and we would expect to find a positive role for size in the adoption probability. For the intensity index, the negative role for size is rather surprising. Unfortunately, measurement error, or selectivity bias, could be at fault here. It is possible that firms with little AMT equipment prefer to answer they have none, in order to avoid answering further detailed survey questions. It is reasonable to expect the censoring to occur below an actual, unobserved, amount of equipment. The intensity index is proportional to a measure of the amount of equipment divided by an measure of aggregate inputs. The small firms which do respond to the AMT question therefore have a high AMT intensity index, while the censoring would mostly occur for the firms with a small index. For this reason, the measured effect of size on intensity could be biased down.

An attempt is made to assess the importance of this problem. Assuming that censoring takes place and that firms that report no AMT usage actually had a value below a threshold, the equation explaining the intensity of AMT usage is then be estimated with a correction for this mismeasurement .

$$y_{1i}^* = X_{1i}'\beta_1 + u_{1i}, \quad y_{2i}^* = X_{2i}'\beta_2 + u_{2i},$$

$$y_{2i} = y_{2i}^* \quad \text{if } y_{1i}^* > 0$$

$$= 0 \quad \text{if } y_{1i}^* \leq 0, \quad i = 1, 2, \dots, n,$$

where $\{U_{1i}, u_{2i}\}$ are i.i.d. drawings from a bivariate normal distribution with mean zero, variances σ_1^2, σ_2^2 , and covariance σ_{12} , y_1 represents the binary variable of AMT usage, and y_2 represents the AMT intensity. In this model, it is assumed that no measurement error is made in the adoption variable, so that the probit analysis of table 7 gives consistent estimates of β_1 . Then the selection bias in β_2 can be corrected using a Heckman two-step estimator. The estimates are obtained by OLS on

$$y_{2i} = X_{2i}'\beta_2 + \sigma_{12}\sigma_1^{-1}\lambda(X_{1i}'\alpha_1) + \epsilon_{2i}, \quad \text{for } i \text{ s.t. } y_{1i} > 0$$

where $\alpha_1 = \beta_1\sigma_1^{-1}$, $E[\epsilon_{2i}] = 0$, and,

$$\text{Var}(\epsilon_2) = \sigma_2^2 - \sigma_{12}^2\sigma_1^{-2}[X_{1i}'\alpha_1\lambda(X_{1i}'\alpha_1) + \lambda(X_{1i}'\alpha_1)^2].$$

The Heckman correction term, $\lambda(X_1'\alpha_1) = \frac{\phi(X_1'\alpha_1)}{\Phi(X_1'\alpha_1)}$, is the ratio of the probability density and the cumulative density, evaluated at $X_1'\alpha_1$.¹²

¹²Alternatively, we could assume that our adoption variable is actually mismeasured because censoring occurs when the total amount of AMT equipment is below a threshold. In this case, the above model is generalized to

The last row of table 8 gives the results for the Heckman correction term, which is seen to be small and insignificant. In other words, the selection problem does not play a significant role, and the coefficients on the other variables in the AMT intensity regression are virtually unchanged when the selection term is not included.

In contrast to most other studies of AMT, it is found that the proportion of advanced equipment in a firm's factor inputs significantly decreases with firms size. Because this and other studies, using binary measures or sums of binary measures find increases in firm size, the decreasing intensity with size is rather novel. The decline of AMT intensity with labor productivity is also a new finding.

4 Employment and Productivity Dynamics

This section looks at the employment and productivity movements between 1985 and 1991 for plants which employed AMT in 1992. It is implicitly assumed that the adoption of technology took place early enough to have an impact on firm dynamics in this period. The effects of the binary choice variable, the AMT-usage index, and the AMT impact variable on firm dynamics will all be evaluated.

As described in section 2, employment growth did not rise more rapidly at AMT using firms than at non-AMT users. However, this is no longer true when the largest five firms are excluded: employment growth is 1-1/2 percentage point per year higher for AMT users. Tables 1 and A.1 also show that labor productivity grew about 1/2 percentage point faster for AMT users than non-users, while TFP declined 1-1/2 percentage points less for AMT users.

Instead of relying on aggregates of the balanced sample, with or without the largest five firms, the effect of AMT usage on average changes in employment is estimated by regressing changes in employment on an AMT dummy, lagged wage, lagged productivity, wage change, productivity change, and size and industry dummies. In the second column of table 9 it is seen that usage of AMT leads to higher employment growth at the firm level, while high wage growth is correlated with employment declines. In the next column, the impact of AMT usage on production is used as an explanatory variable. This variable describes the subjective effect on a firm's production in

the case where Y_1^* is a continuous, unobserved, variable, and $Y_1 = 0$ when the unobserved amount of equipment is small.

$$\begin{aligned} y_{1i}^* &= X_{1i}'\beta_1 + u_{1i}, & y_{2i}^* &= X_{2i}'\beta_2 + u_{2i}, \\ Y_{1i} &= y_{1i}^* & \text{if } y_{1i}^* > c \\ &= 0 & \text{if } y_{1i}^* \leq c, \quad i = 1, 2, \dots, n, \\ y_{2i} &= y_{2i}^* & \text{if } y_{1i}^* > c \\ &= 0 & \text{if } y_{1i}^* \leq c, \quad i = 1, 2, \dots, n, \end{aligned}$$

where c is the threshold of observation, and the rest is as given above. Since the Heckman term in the first case was seen to be insignificant, this variant was not further explored.

the case of failure of the AMT equipment. The positive employment effect is seen to increase in the firm's assessment of the importance of the equipment. In the third column, however, it is seen that even though usage of AMT increases employment growth, the intensity of use does not add to this effect.

The next three columns of table 9 show the results for similar regressions of changes in labor productivity on AMT usage, impact, and intensity and other variables. In contrast to the aggregate positive relation between AMT usage and labor productivity growth, our regressions show no significant effect of AMT on average productivity growth at the firm level. Changes in employment are negatively correlated with productivity growth, while growth in wages is positively correlated. The finding of no significant effect of AMT on productivity is rather striking. In general labor productivity can be improved by mere capital deepening, even though it may not be an optimal reallocation of resources. If employing AMT indicates recent acquisition of capital, it seems that this should be correlated with improvements in labor productivity. The coefficient on increases in the capital-labor ratio are very significant, and may not leave any room for a separate AMT effect.

The intensity variable is not seen to have much effect, on average, on employment growth, conditional on adoption. The insignificant effect could be the result of two opposing effects. On the one hand, the intensity is driven by the technology which is necessary to produce the types of goods which are desired in the marketplace. The jobs losses owing to more efficient production at the 'successful' companies which heavily use AMT is made up by job gains through increases in market share. This is explored further below.

Table 10 shows the relationship between changes in employment and productivity for AMT and non AMT users, as well as for different categories of AMT impact and intensity. The second and third columns of the table show the changes in labor productivity and employment, respectively. The last four columns show the share of total employment for each row in four groups of firms split by changes in employment and productivity.¹³ The first group contains firms where both employment and labor productivity increased between 1985 and 1991, the second group contains firms with declining employment and increasing productivity, in the third group, both employment and productivity decline, while in the last group employment increased while productivity declined.

Employment and productivity growth is higher for AMT users, and the percentage of employment in the first group, the 'successful upsizers', was higher for users of AMT equipment. Employment growth increases for AMT users as the impact of the technology on production increases. Also, the proportion of successful **upsizers** is larger for firms reporting complete production stoppage due to equipment failure, than for the firms which report little or no effect. The intensity

¹³These groups were used by Baily et al. (1995) to describe succesful and unsuccessful upsizers and downsizers. For the Netherlands, this analysis was replicated by Bartelsman et al. (1995).

Table 9: Changes in Employment, and Labor Productivity

Variable	AE			AII		
Constant	8.729 (1.643)	8.533 (1.645)	8.860 (1.668)	3.015 (1.274)	2.815 (1.278)	-0.397 (0.037)
AMT-Dummy	1.128 (0.389)		1.273 (0.423)	-0.145 (0.297)		0.012 (0.009)
AMT Intensity			-0.142 (0.137)			0.003 (0.003)
Nihil		0.580 (0.819)			-0.052 (0.627)	
Marginal		1.034 (0.484)			0.134 (0.371)	
Significant		1.403 (0.468)			0.119 (0.359)	
Complete		1.960 (0.753)			-0.137 (0.577)	
Exp/Sales	-1.820 (0.641)	-1.857 (0.642)	-1.806 (0.651)	-1.199 (0.499)	-1.209 (0.499)	0.003 (0.015)
Wage growth	-0.563 (0.056)	-0.557 (0.056)	-0.570 (0.056)	0.646 (0.042)	0.646 (0.042)	0.019 (0.001)
K-L growth	0.065 (0.016)	0.063 (0.016)	0.065 (0.016)	0.060 (0.012)	0.058 (0.013)	-0.003 (0.000)
Exp/S growth	0.024 (0.016)	0.023 (0.016)	0.024 (0.016)	-0.003 (0.012)	-0.003 (0.012)	-0.000 (0.000)
Prod. growth	-0.229 (0.034)	-0.231 (0.034)	-0.227 (0.035)			
Size Dummies						
20-49	1.850 (0.596)	1.801 (0.597)	1.859 (0.601)	0.371 (0.458)	0.333 (0.460)	0.015 (0.013)
50-99	2.495 (0.638)	2.395 (0.641)	2.426 (0.644)	0.383 (0.491)	0.298 (0.494)	0.006 (0.014)
100-199	0.832 (0.684)	0.709 (0.687)	0.782 (0.694)	0.091 (0.526)	-0.021 (0.530)	-0.005 (0.015)
200-499	-0.275 (0.772)	-0.447 (0.777)	-0.224 (0.783)	0.481 (0.596)	0.362 (0.601)	-0.011 (0.017)
500 +	0.207 (1.048)	0.012 (1.055)	0.144 (1.062)	0.331 (0.801)	0.170 (0.808)	-0.049 (0.023)
R ²	.22	.22	.21	.27	.27	.27

Standard errors parenthesis. Industry dummies in

Table 10: Employment and Productivity Changes, by Quadrant, 85-91

Category	AI-I'	ΔE^2	Quad I	Quad II	Quad III	Quad IV ³
All Plants	2.5827	1.7673	41.31	26.51	6.66	25.53
AMT Usage						
AMT=0	2.2193	0.8743	37.39	29.21	6.54	26.86
AMT=1	2.6856	2.0427	42.51	25.67	6.69	25.12
AMT Impact						
Nihil	2.6753	1.1822	31.41	38.78	4.41	25.40
Marginal	1.8153	1.2638	44.32	21.62	8.22	25.85
Significant	2.7673	2.2678	40.89	28.53	6.05	24.53
Complete	2.5114	3.3778	52.87	18.26	5.05	23.82
AMT Intensity						
1st Quintile	2.7100	1.3706	35.02	28.95	6.58	29.45
2nd Quintile	4.3767	2.2965	49.84	29.75	5.17	15.24
3rd Quintile	2.8034	0.0257	61.14	21.43	17.42	0.00
4th Quintile	2.3204	1.9963	46.23	23.98	10.27	19.52
Top Quintile	2.1355	2.6587	43.92	21.60	5.08	29.40

I: $\Delta \Pi > 0, \Delta E > 0$; II: AI-I > 0 , AE < 0 ;

III: AI-I < 0 , AE < 0 ; IV: AI-I < 0 , AE > 0

¹ Within-group aggregate labor productivity growth.

² Within-group aggregate employment growth.

³ Percent of total employment in each Quadrant.

measure, on the other hand, shows no clear pattern for employment and productivity growth or for assignment to quadrants.

5 Conclusions

This paper presented a first investigation into the role played by advanced manufacturing technologies in Netherlands industry. It was found that the probability that a firm used AMT equipment increased with firm size and the capital-labor ratio. Conditional on AMT usage, the intensity of usage increased with the capital-labor ratio, but declined with the level of labor productivity. Further, the intensity declined with firm size, even after correcting for possible sample selection bias.

The effects of AMT on firm performance are more complex. Firms which use AMT have higher employment growth on average, and as a group have higher employment growth than non-users when the largest five firms are excluded. Conditional on adoption, the employment impact increases with the subjective importance of the AMT impact, but does not vary with AMT intensity. Labor productivity growth increases about 1/2 percentage point more per year for the AMT using firms than for the others, but on average, the AMT effect is insignificant. Mostly, it is the increase in the capital-labor ratio which is seen to improve labor productivity.

In future work, the relationship between capital deepening and AMT usage will be explored

further. The AMT choice likely takes place as part of an investment decision, which in turn depends on the relative position of the firm with regard to productivity and wages. In this framework, it becomes possible to trace the declining pattern of the cost-benefit ratio of AMT vs. traditional equipment.

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Table A.I: Summary Statistics, PS85, PS91, AMT92

		All Firms ^f	PS85-PS91	PS85-PS91-AMT92		
				All	AMT=0	AMT=1
Firms	1991	14301	6116	1430	614	816
Firms	1985	9058				
output=	1991	290567	248529	70694	15748	54946
output	1985	237906	205404	54454	13080	41374
Output Growth			3.23	4.45	3.14	4.84
V.Add ^a	1991	80841	53483	16082	3123	12959
V.Add	1985	59616	51865	15137	3309	11829
V.Add Growth			0.51	1.01	-0.96	1.53
Employment [*]	1991	788626	642867	189336	43439	145897
Employment	1985	689624	580229	170287	41219	129068
Empl. Growth			1.72	1.78	0.88	2.06
Wage ^b	1991	60	61	60	56	61
Wage	1985	56	57	55	52	56
Wage Growth			1.26	1.41	1.04	1.49
Productivity [*]	1991	368	387	373	363	377
Productivity	1985	345	354	320	317	321
Prod. Growth			1.48	2.62	2.24	2.72
TFP Growth			-1.79	-1.65	-2.80	-1.31
K-L Ratio ^c	1991	354	312	312	174	353
K-L Ratio	1985	229	221	216	150	237
K-L Growth			5.96	6.31	2.51	6.85

^a Thousands, 1985 Guilders
^b Number of Employees
^c Thousands, 1985 Guilders
^d Output per employee, thousands, 1985 Guilders
^e Gross capital stock per employee, thousands, 1985 Guilders
^f The 1991 PS includes firms with less than 20 employees

CHART 1
CAM Penetration by 1991

CHART 2

CC Adoption Probabilities