TECHNOLOGY DIFFUSION IN U.S. MANUFACTURING: THE GEOGRAPHIC DIMENSION

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"Technology" is a key determinant of growth, but economists frequently leave its components jumbled together in Rosenberg's black box. In neoclassical models, we let the residuals represent technology and, waving our hands, treat technical progress as "manna from heaven." And, while the endogenous growth approach explicitly seeks to model the production of technology, the customary use of R&D spending to represent technological change has serious drawbacks. Not all R&D spending is equally productive, for instance, and a significant portion relates to the invention of new consumer products (product innovation). While product innovation may well influence national or regional business cycles and improve consumer welfare, this type of innovation generally has fairly minor effects on factor productivity. By contrast, the invention of new types of capital equipment or new production methods (process innovation) *is* a key determinant of the production frontier. After all, the state of scientific and technical knowledge sets the limits. Nevertheless, the invention of new capital equipment or manufacturing methods represents just one step in the evolution of prevailing production procedures.

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A second critically important determinant of dominant manufacturing practice is the manner in which state-of-the-art technology enters general use. If the speed, intensity, and uniformity with which advanced technologies are adopted vary across nations and regions, these differences will affect the extent to which (or the pace at which) long-term growth rates converge. Views about the ease and pace of technology diffusion differ. Boyan Jovanovic (1995) suggests, for example, that the repetitive process by which each adopting firm learns about and incorporates a new technology into its operations generally consumes a larger share of national income than innovation itself.[1] By contrast, in neoclassical models, the acquisition of frontier technology occurs without delay or cost.

If the neoclassical assumption applies anywhere, that place is surely the United States, given the flow of labor, capital, and information among the U.S. states. Yet, Barro and Sala-i-Martin (1991) and others have found that per capita output converges at a 2 to 3 percent annual rate across the U.S. states, a pace far too slow to conform to neoclassical predictions for a closed, much less an open, economy.[2] While Barro, Mankiw, and Sala-i-Martin (1995) explain this surprisingly slow convergence by incorporating differences in human capital and a requirement that investment in human capital be financed locally, variations in technology adoption might also play a role. Thus, examining actual patterns in technology use across the U.S. states could be informative. Moreover, identifying any environmental characteristics that impede or accelerate technological diffusion would improve our understanding of the growth process and could have useful policy implications.

Accordingly, this paper explores the geographic dimension of technology diffusion in U.S. manufacturing. Using relatively new data from the Census Bureau's Surveys of Manufacturing Technology (SMTs) for 1988 and 1993, it examines variations in the adoption of 17 advanced technologies across the nation and within individual U.S. states.[3] It asks, in particular, whether proximity to firms already using high-tech equip-

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[1] Similarly, Lucas (1993) concludes that a key characteristic distinguishing fast-growing developing countries from slow-growth ones is an ability to adopt increasingly sophisticated production methods and to move along successive learning curves. He suggests that openness to trade supports such an ability.

[2] Cogley and Spiegel (1996) reconfirm this finding using time-series methods and Monte Carlo techniques to improve the precision of the estimates. While Barro and Sala-i-Martin found a somewhat faster rate of convergence (4.6 percent annually) for manufacturing output, this pace remains slow for a neoclassical world with capital mobility.

[3] The SMT covers the use of the 17 advanced technologies listed and described in Appendix 1 at firms with 20 or more employees in the fabricated metals, industrial machinery and equipment, electronic and other electric equipment, transportation equipment, and instruments and related products industries (SIC codes 34-38).

ment fosters adoption, but it also seeks to distinguish other plant and locational characteristics linked to increased probability of technology use.

The paper is organized as follows. The first section discusses why technology use might be expected to vary by geographic area. It distinguishes the influence of locational characteristics, like the availability of skilled workers, from the impact of proximity to other high-tech users. It also points to reasons, like the prevalence of multi-establishment firms, why technology use might be remarkably evenly distributed in the United States. The next section describes the SMT and other Census data bases used in the study, while the third discusses the use of the SMT for geographical analysis and presents some summary tables and maps. The fourth section presents the econometric models used to examine the speed of technology adoption between 1988 and 1993. While this analysis focuses on the impact of proximity to other technology users on the speed of adoption, the models also control for plant and geographic characteristics. The final section offers conclusions.

WHY GEOGRAPHY MIGHT MATTER

The use of advanced technologies could vary considerably by state and region for many reasons, such as differences in access to skilled labor or industrial concentration and in the applicability of technologies across industries. As might be expected, for instance, given the auto firms' reputation for close ties to their suppliers, the SMT for 1993 shows that almost one-fourth of the establishments in transportation use intercompany computer networks to link plants with suppliers and customers, whereas only 15 percent of industrial machinery plants have adopted this technology. Similarly, since electronics firms have successfully adapted pick-and-place robots to set chips on semiconductors, the electronics industry reports the greatest use of this equipment; by contrast, transportation plants are the heaviest users of "other" robots.

To illustrate the differences in industrial concentration across the nation, Map 1 shows the share of manufacturing employment in each metropolitan and broader non-metro area[4] accounted for by firms with 20 or more workers in SICs 34 through 38 (the SMT sample population), while Table 1 shows how the use of the 17 advanced technologies examined in the SMT varies across these industries. Map 2 depicts regional variations in the educational attainment of the labor pool, presumably an important locational consideration.

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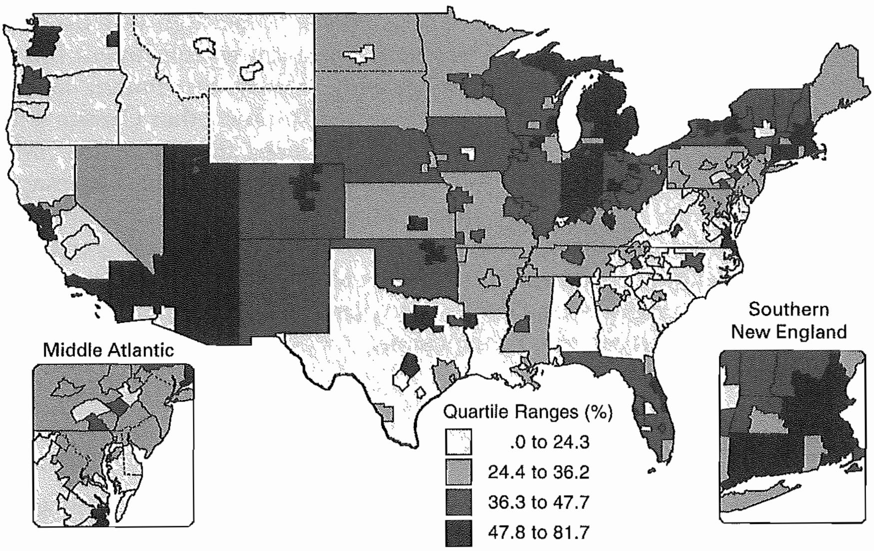
[4] For reasons discussed below, we combine non-metropolitan areas within a state into "quasi-MSAs" (QMSAs); in some cases, QMSAs include small metro counties or combine non-metro areas across state borders.

Map 1
Share of Manufacturing Employment in Establishments with 20+ Employees, SICs 34 to 38, 1987



Note: Regions are MSAs and QMSAs, defined in the text.
Source: U.S. Bureau of the Census, *County and City Data Book, 1994.*

Yet another explanation for regional differences in technology use may be that many of the advanced technologies covered by the SMT, particularly those linked to flexible manufacturing, are especially useful to firms with varied output and short production runs, since this equipment reduces down times and set-up costs. But branch plants with standardized output and long production runs and plants making a variety of innovative or niche products tend to locate in different areas. For branch plants, minimizing labor costs and transportation to mass markets may be crucial, whereas plants producing customized items or prototypes may require a more highly skilled labor force or frequent contact with product designers at headquarters.

These variations in the applicability of technologies, combined with a clustering of plants by industry or stage of product cycle, may explain some geographic differences in technology use; however, these explanations are distinct from the possible impact of proximity to other plants

Table 1
Share of Establishments Using Selected Manufacturing Technologies in 1993, by Industry
Percent

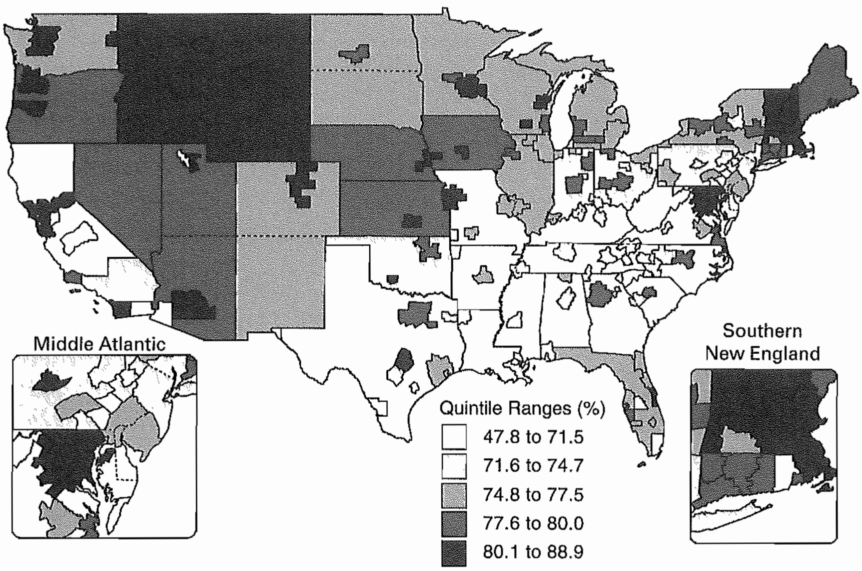
Technology	Fabricated Metals	Industrial Machinery	Electronic and Other Electrical Equipment	Transportation Equipment	Instruments and Related Products
Design & Engineering					
CAD or CAE	46.5	64.1	64.2	53.9	65.5
CAD to Control Machines	19.3	34.8	21.5	25.5	18.5
CAD Used in Procurement	7.0	11.6	16.1	9.6	16.1
Fabrication/Matching Assembly					
Flexible Manufacturing Cells/Systems	9.5	11.8	17.0	15.5	14.2
NC or CNC Machines	40.4	61.9	34.5	44.1	35.1
Materials Working Lasers	3.4	4.3	7.8	5.4	6.3
Pick-and-Place Robots	6.6	5.4	15.2	10.1	11.7
Other Robots	3.8	3.6	5.3	11.7	3.8
Automated Material Handling					
Automatic Storage/ Retrieval	1.2	2.3	3.8	3.8	4.8
Automatic Guided Vehicle Systems	.3	1.1	1.7	2.2	1.5
Sensor-Based Inspection/Testing					
For Incoming or In-Process Materials	8.1	8.1	11.8	15.6	11.7
For Final Product	9.6	10.6	17.5	16.2	14.7
Communication and Control					
LAN for Technical Data	20.1	29.4	37.1	28.0	40.7
LAN for Factory Use	14.5	21.0	30.5	23.9	30.0
Intercompany Computer Network	16.7	15.4	21.9	23.4	15.3
Programmable Controllers	30.2	29.0	30.7	30.7	29.8
Computers Used to Control Factory Floor	20.2	28.1	33.2	26.8	29.0

See Appendix for descriptions of technologies.

Source: U.S. Bureau of the Census, *Manufacturing Technology: Prevalence and Plans for Use 1993*, SMT (93)-3, U.S. Government Printing Office, Washington, D.C., 1994.

using advanced technologies. Why might nearness to plants already using high-tech equipment exert an independent effect on adoption decisions? Because early adopters "infect" other firms. Or, more precisely, because closeness to plants already using advanced technologies is likely to reduce the perceived risk and actual cost of investing in this

Map 2
Share of Population Age 25+ with High School Diploma or Higher, 1990



Note: Regions are MSAs and QMSAs, defined in the text.
Source: U.S. Bureau of the Census, *County and City Data Book, 1994.*

new equipment.[5] A firm incorporating new technology into its production function faces significant costs. Management must learn about a technology, assess the costs and benefits of this often lumpy investment for its own operations, look for the best vendor, adjust the plant's manufacturing operations to accommodate the new equipment, and possibly modify the new equipment to fit the plant's needs. The adoption costs also include a loss of human capital acquired in using the old equipment and reduced productivity while employees work their way down a new learning curve.

Proximity to firms already using a new technology is likely to reduce the apparent riskiness and other costs of investing in this new equipment because it permits process engineers and management staff to observe the equipment in operation at nearby facilities and to discuss the

[5] Aizenman (1995) demonstrates that uncertainty acts as an implicit tax on new activities.

advantages and disadvantages of its use. These neighbors may also have helpful advice about specific vendors, and about problems encountered in introducing the equipment onto the shop floor.[6] Because adopting advanced technologies usually requires changing manufacturing procedures—possibly even the plant layout—the process generally requires considerable engineering input. Accordingly, location near a pool of engineers experienced in using this equipment could cut adoption costs. Similarly, access to a pool of production workers with knowledge of these technologies could also lessen the required investment in human capital. As a final external economy, a cluster of plants using advanced technologies might draw firms supplying support services and parts.[7] In other words, all the Marshallian agglomeration economies pertain.

On the other hand, several forces could be operating to dilute the impact of proximity and promote an even distribution of technology across the United States. First, equipment vendors promote their wares nationwide in business media and at trade shows. Vendors actively try to eliminate any technological backwaters they can find. In addition, many plants are part of a multi-establishment firm and benefit from experience with new technologies at related facilities. Then too, defense contractors and subcontractors are generally required to use many of the technologies covered by the SMT. While many areas are considerably more dependent on defense work than others, these requirements are actually intended to encourage technology diffusion as well as to ensure the quality of military procurement (Rees, Briggs, and Oakey 1984; Knudsen, Jacobs, Conway, and Blake 1994). Finally, several of the technologies covered by the SMT have been available long enough to allow their adoption wherever they are relevant. In particular, numerically controlled (NC) machines, which are not distinguished from computer numerically controlled machines (CNC) on the SMT questionnaire, have been widely used for decades.

Existing evidence on the impact of proximity on technology use is slim. In a recent *American Economic Review* article, Ciccone and Hall (1996) found that productivity is positively associated with employment density across states, a result consistent with the hypothesis that proximity to users spurs technology adoption. More directly relevant is work by or cited by Nadiri (1993), who finds evidence of large externalities from R&D activities and suggests that the spillovers could occur via intra- or inter-industry channels, customer-supplier relations, or geographic location. In addition, Jaffe, Trajtenberg, and Henderson (1993) and Jaffe

[6] As Nooteboom (1993) and Wozniak (1993) point out, informal contacts and chance meetings may be particularly important in the case of small, single-establishment firms and early adopters.

[7] Alternatively, a cluster of firms using advanced technologies may grow up around manufacturers of high-tech equipment—machine tool makers or software developers, for instance. See Assembly of Engineering (1981).

(1995) use patent citations to trace significant spillovers from local patenting activity. They find that, excluding self-referrals, patent citations are two to six times more likely to occur within the same SMSA and two times more likely to occur within the same state, compared with the results for a control group. Similarly, Audretsch and Feldman (1996) find that product innovation clusters even when they control for concentration in production activity. But, as mentioned earlier, invention differs from adoption.

Maintaining this distinction, another body of work has found that location in a metropolitan area promotes product innovation but not necessarily process innovation or advanced technology use. Davelaar and Nijkamp (1989), for example, examined the generation of product and process innovation among Dutch manufacturers and found that location in highly urban areas was important to product but not to process innovation. Similarly, Harrison, Kelley, and Gant (1996) studied the adoption of programmable automation among U.S. metalworking firms and concluded that the likelihood of adoption was significantly associated with location in metropolitan suburbs and edge cities rather than in an urban core or rural area. They also found no association with proximity to clusters of firms in the same industry. Moreover, Rees, Briggs, and Oakey (1984) noted evidence of regional contagion in the use of NC and CNC machines for small plants or single-establishment firms, but not for their entire sample. They attributed the positive impact of location in the North Central region to this area's history as the center of the machine tool industry. Finally, in a study on the use of advanced manufacturing technologies in Canada, based on a Canadian version of the SMT, McFetridge (1992) noted that establishments in Quebec and Ontario were somewhat more likely to adopt some technologies than were plants in the Atlantic or western parts of the country.

The limited amount of econometric work on the role of geography in the adoption process undoubtedly reflects the lack of a comprehensive micro-level data base with a direct measure of technology use. With the exception of McFetridge, all of the studies cited in the preceding paragraph were based on comparatively small, one-time surveys. As the 1993 SMT summary publication points out, "information on technology use was in great demand and short supply" until the late 1980s (U.S. Bureau of the Census 1994). But, starting in 1988, the Surveys of Manufacturing Technology improved the situation dramatically.

What We Have Learned from the SMT to Date

The SMTs and the data bases linked to them provide a wealth of information to researchers interested in technology, growth, and productivity issues. These surveys are designed to obtain a reliable reading on the use of 17 advanced technologies in five groups (design and engineering; fabrication/machining and assembly; automated materials handling;

automated sensor-based inspection and testing equipment; and communications and control) at establishments with 20 or more employees in SIC codes 34 to 38.[8] The first survey, conducted in 1988, was based on 10,526 establishments representing a universe of 39,556, while a follow-on survey, done in 1993, was based on 8,336 units representing 42,991 establishments (accounting for over 40 percent of employment and value added in the 1987 *Census of Manufactures*).[9] The samples were stratified by 3-digit SIC code and three employment-size groups (20–99; 100–499; and 500 and above) and drawn from the 1987 *Census of Manufactures* by simple random sampling within strata.[10] Within each stratum, thus, each establishment had an equal chance of being selected. The establishment count for each cell in the summary publications (and this paper) is a simple weighted estimate, where the establishment weights are the inverse of the sampling fraction.[11]

Tables 2 and 3 present summary data drawn from the 1993 SMT. Table 2 shows the number of establishments and the percentage using at least one and at least five advanced technologies, broken down by industry, size, age, manufacturing process, and whether or not the plant produces to military specification. This summary table immediately suggests that technology use increases with plant size (but not necessarily with age) and is greatest at establishments that combine fabrication and assembly work and that produce to military specification.

Table 3 shows the percent of establishments using each of the 17 technologies and when they first adopted them. As the table suggests, the usage rates vary considerably from highs of 59 percent for computer-aided design and engineering and 47 percent for numerically and computer numerically controlled machines to lows of less than 3 percent for automated materials handling equipment. It is also clear that most of the machining, materials handling, and inspection technologies were introduced by the largest share of users before 1988, whereas most of the computer-aided design and engineering and communication and control technologies were introduced between 1988 and 1991. Only in the case of

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[8] Appendix 1 lists and describes the 17 technologies. The industries covered by SIC codes 34 to 38 include: fabricated metal products; industrial machinery and equipment; electronic and other electric equipment; transportation equipment; and instruments and related products.

[9] An SMT survey conducted in 1991, "Manufacturing Technology: Factors Affecting Adoption," was not designed to follow up the 1988 survey; it does not cover one of the technology groups included in the 1988 and 1993 surveys (communications and control), and it asks a different set of questions. Issues covered concern factors affecting the decision to adopt, intensity of use, time required to achieve full operation, barriers and benefits to adoption, and problems encountered with technology use.

[10] In some sparsely inhabited cells, the entire population was surveyed.

[11] In this paper, the weights are normalized within each area by a region-specific normalization factor. Accordingly, weighted data should not be biased by differences in probability of sample inclusion across strata. See Appendix 2 for further discussion.

Table 2
Manufacturing Technology Use in 1993, by Establishment Characteristic

Characteristic	Number of Establishments	Using at Least 1 Technology (%)	Using at Least 5 Technologies (%)
All Establishments	42,991	75.0	29.1
Industry			
Fabricated Metals	13,190	67.1	22.3
Industrial Machinery	14,231	81.5	30.2
Electronic & Other Electrical Equipment	7,472	78.8	35.6
Transportation Equipment	4,110	68.7	33.2
Instruments	3,988	78.0	31.1
Employment Size			
20 to 99	30,502	69.1	18.3
100 to 499	10,321	89.3	50.3
500 & over	2,168	90.6	80.2
Age of Plants (years)			
Less than 5	4,893	82.9	23.4
5 to 15	13,722	81.2	30.9
16 to 30	11,303	83.4	32.6
Over 30	9,310	80.3	36.7
Not Specified	3,763	4.1	.5
Manufacturing Process			
Fabrication/Machining	6,795	80.3	26.9
Assembly	6,388	79.9	26.9
Both	23,393	85.7	36.6
Neither	2,577	56.3	13.4
Not Specified	3,838	5.3	1.1
Products Made to Military Specification			
Yes	14,112	88.9	39.5
No	22,214	78.4	28.0
Don't Know	2,939	73.9	23.6
Not Specified	3,726	3.3	.4

Source: U.S. Bureau of the Census, *Manufacturing Technology: Prevalence and Plans for Use 1993*, SMT (93)-3, U.S. Government Printing Office, Washington, D.C., 1994, Table 1, pp. 5–6.

intercompany computer networks linking plants with suppliers, subcontractors, and customers were adoption rates increasing in the most recent period. Moreover, and surprisingly perhaps, the use of robots other than pick-and-place, automated material handling systems, and programmable controllers actually declined between 1988 and 1993. As McGuckin, Streitwieser, and Doms (1995) suggest, technology may be an "experience good" involving much trial and error. In addition, some establishments

Table 3
Share of Establishments Using Selected Technologies in 1993, by Time of Adoption
Percent

Technology	Establishments Using in 1993	Adopting in Past 2 Years	Adopting in Past 2 to 5 Years	Adopting 5+ Years Ago
Design & Engineering				
CAD or CAE	58.8	12.4	26.2	19.4
CAD to Control Machines	25.6	5.9	10.9	8.4
CAD Used in Procurement	11.3	3.8	4.8	2.3
Fabrication/Machining				
Flexible Manufacturing Cells/Systems	12.7	3.9	4.7	3.8
NC or CNC Machines	46.9	4.4	11.7	29.6
Materials Working Lasers	5.0	1.5	1.3	2.0
Pick-and-Place Robots	8.6	1.9	3.0	3.4
Other Robots	4.8	.9	1.8	1.9
Automated Material Handling				
Automatic Storage/Retrieval	2.6	.5	.9	1.1
Automatic Guided Vehicle Systems	1.1	.2	.4	.5
Sensor-Based Inspection/Testing				
For Incoming or In-Process Materials	9.9	2.4	3.5	3.6
For Final Product	12.5	3.0	4.3	4.7
Communication and Control				
LAN for Technical Data	29.3	10.0	12.0	6.0
LAN for Factory Use	22.1	7.8	8.2	5.3
Intercompany Computer Network	17.9	7.4	6.1	3.6
Programmable Controllers	30.4	5.2	10.2	13.4
Computers Used to Control Factory Floor	26.9	7.1	10.0	8.6

See Appendix for descriptions of technologies.

Source: U.S. Bureau of the Census, *Manufacturing Technology: Prevalence and Plans for Use 1993*, SMT (93)-3, U.S. Government Printing Office, Washington, D.C., 1994.

may be eliminating some of the older technologies as they gradually update their facilities—replacing programmable controllers, say, with CAD/CAM systems. (See Beede and Young (1996) on possible technology ladders within the SMT group.)

To add to the researcher's cornucopia, the plant-specific data on technology use from the SMT can be matched with information in the Longitudinal Research Database (LRD) to trace individual establishments covered by the Annual Surveys and Censuses of Manufactures over time.[12] The SMT can also be linked to the Worker-Employer Characteristics Database (WECD), not used in this paper, which matches employee data for individuals filling out the long form for the 1990 Census of Population with establishment-level data from the Census of Manufactures. Finally, firm identifiers allow linking individual establishments to the appropriate firm.[13]

Studies based on the SMT and related data bases have already addressed a number of important issues. (See Alexander (1994) for a survey of this work.) For instance, Dunne (1994) finds that use of advanced technologies rises with plant size but is relatively uncorrelated with age, a result supporting the use of models that allow firms to upgrade their capital base. Dunne and Schmitz (1995) use the SMT to examine the large wage premium associated with large employer size, a link that has intrigued researchers for some time. They find that technically advanced plants pay higher wages and employ a greater fraction of non-production (presumably more highly skilled) workers; they also conclude that use of advanced technologies accounts for a significant part of the size-wage premium.[14] Noting that use of advanced technologies has been positively linked to measures of plant performance like productivity, sales and employment growth, and survival rates, McGuckin, Streitwieser, and Doms (1995) conclude that the primary explanation for these cross-section relationships is that well-managed plants adopt new technologies, not that these technologies clearly improve plant performance. Similarly, Doms, Dunne, and Troske (1995) find that technologically advanced plants employ a larger share of highly skilled and highly paid[15] workers both before and after adopting high-tech equipment. While adopting new technologies may increase the demand for skilled workers, they could not find much correlation between the change in plant-level skill mix and technology use.[16,17]

[12] The LRD contains linked data on 300,000 to 400,000 individual manufacturing plants covered by the Census of Manufactures from 1963 on. It also contains linked data from Annual Survey of Manufactures samples starting with 1972.

[13] Access to these confidential establishment- and firm-level data bases requires affiliation with the Census Bureau's Center for Economic Studies and careful attention to their disclosure procedures.

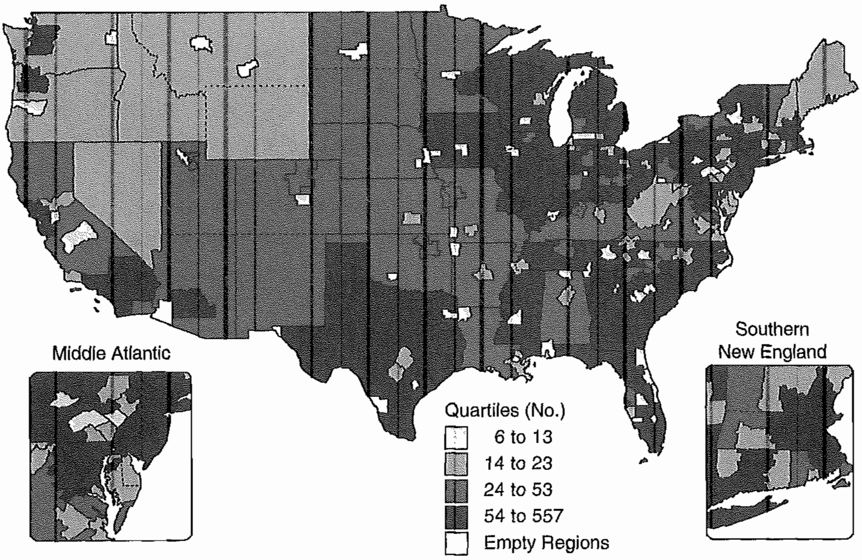
[14] Reilly (1995) draws a similar conclusion about the impact of computer use on the size-wage premium. See also, Davis and Haltiwanger (1991) who, using the LRD and the WECD, find continuously expanding size-wage differentials after 1967. They also attribute rising wage inequality in the United States to skill-biased technical change.

[15] Doms, Dunne, and Troske (1995) find that including quality measures from the WECD mutes but does not eliminate the wage premium associated with use of advanced technologies.

[16] Their study was based on a relatively small sample of plants answering both the 1988 and 1993 SMTs and linked to the WECD.

[17] Sheffrin and Triest (1995) suggest methods for determining the direction of causality in growth models.

Map 3
Number of Observations in 1993 SMT, by QMSA



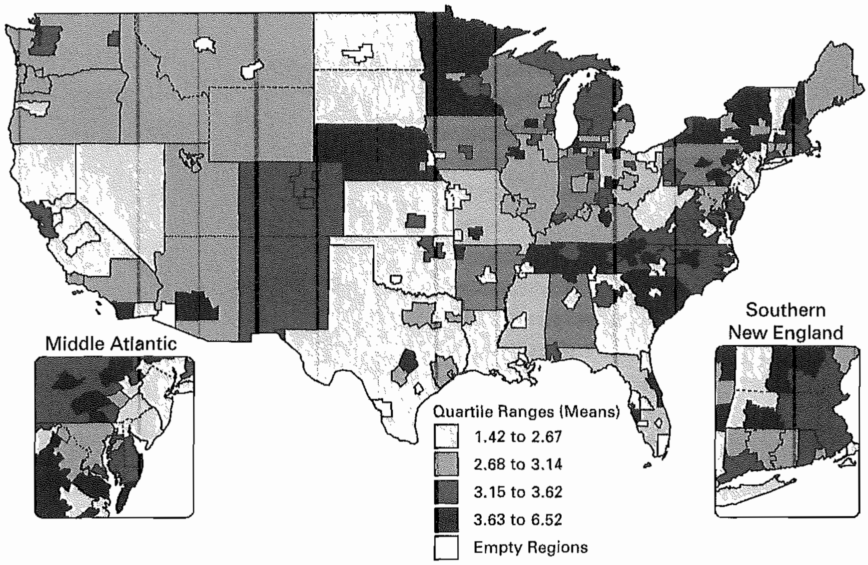
Note: Regions are MSAs and QMSAs, defined in the text.
Source: U.S. Bureau of the Census, Survey of Manufacturing Technology, 1993.

USING THE SMT TO EXPLORE GEOGRAPHIC ISSUES

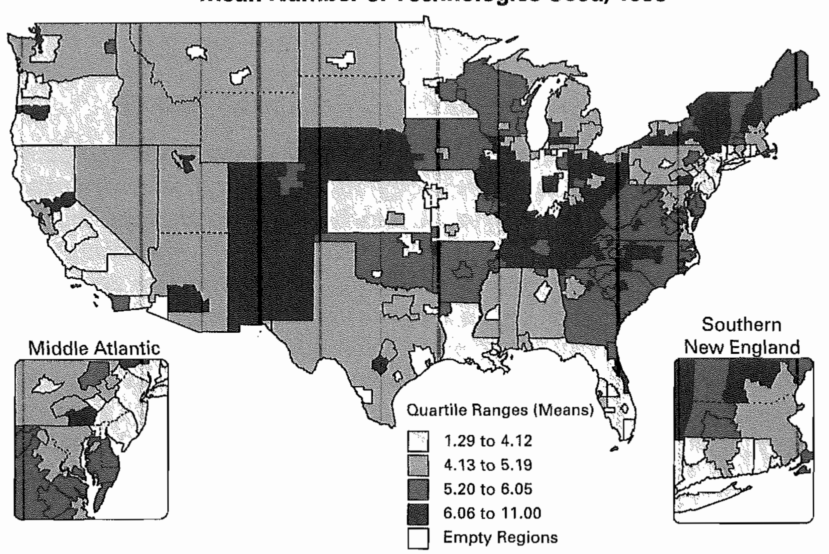
To date, studies based on the SMT have not examined the impact of locational characteristics on technology use, although several authors note that their statistical analysis has included dummies for the nine Census regions (in addition to industry dummies).[18] Accordingly, an extremely important issue becomes defining the appropriate geographic unit for analysis. Over how big an area should the educational attainment of the labor force or proximity to other technology users be measured, for example? Clearly, states often incorporate more than one labor market, and many are too large to be relevant to the issue of proximity. However, in most non-urban (and many urban) counties caught in the SMT net, the SMT sample size is too small to allow meaningful analysis or to meet disclosure constraints. Accordingly, we chose to focus on metropolitan statistical areas (CMSAs and MSAs) and a construct that combines all

[18] Although some papers mention that the regional dummies were statistically significant as a group, they generally do not provide results for the individual regions.

Map 4
Mean Number of Technologies Used, 1988 [a]



Map 5
Mean Number of Technologies Used, 1993 [a]



[a] Based on weighted data.
Note: Regions are MSAs and QMSAs, defined in the text.
Source: U.S. Bureau of the Census, Survey of Manufacturing Technology, 1988 and 1993.

the non-metro counties in a state (a construct called quasi- or QMSAs).[19] Even then, some 150 MSAs or QMSAs did not meet Census disclosure requirements or our own analytic criteria. In these cases, we merged small-sample MSAs with an adjacent QMSA and small-sample QMSAs with similar rural areas across a state border. As a result, we ended with 154 MSA/QMSAs, none of which had fewer than 6 observations in 1988 or 1993.[20] Map 3 shows the location of the well and less well sampled regions for 1993, while Appendix 3 shows the distribution of QMSAs by number of observations contained. Both suggest that the QMSAs with few observations are located in areas with little manufacturing activity and represent a small part of the information available for analysis.

Maps 4 through 7 provide a first visual impression of the variations in technology use across the nation and of how that usage changed between 1988 and 1993. Three caveats are in order. First, these maps do not account for differences in industry mix, plant size, or other characteristics known to influence technology adoption. In addition, in areas with small samples, chance variation may have produced misleading results. Finally, the maps relate only to technology use by establishments in SICs 34 to 38; they tell us nothing about technology use in chemicals or plastics, for instance, or in business or financial services.

To start with one broad measure of technology use, Maps 4 and 5 show the mean number of technologies used by establishments in the SMT population in 1988 and 1993, by QMSA.[21] Unfortunately, the SMTs for 1988 and 1993 provide little information on the intensity with which these technologies are used.[22] However, using the 1991 SMT, which asks about the share of operations dependent on advanced technologies, Doms, Dunne, and Roberts (1995) found that number of technologies used is positively correlated with intensity of use and that number used is a good proxy for intensity. Still, it should be noted that some technologies, like "other" robots and automated materials handling systems, appear to be relevant only to a small number of large plants in a couple of industries. More important, some of these technologies are substitutes; thus, plants are likely to use both only when they are experimenting or shifting from one to another.

One impression emerging from the maps is that technology diffusion

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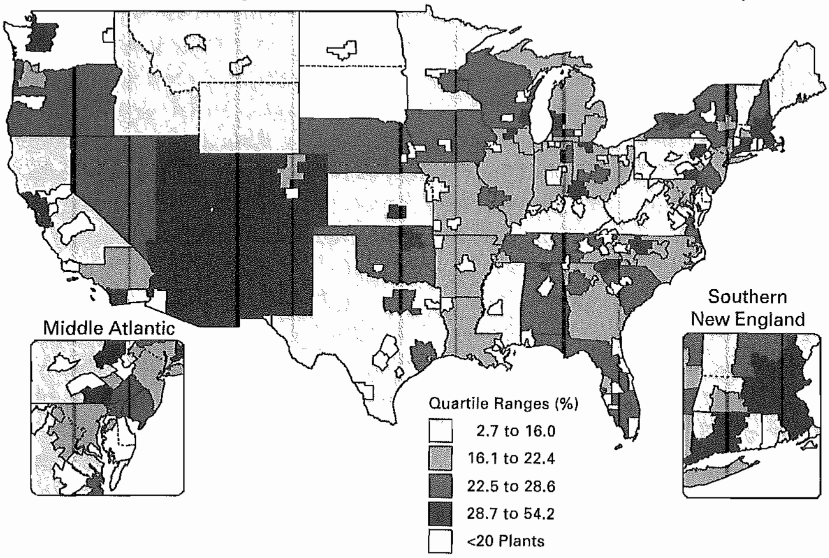
[19] Jaffe, Trajtenberg, and Henderson (1993) used a similar construct which they called "phantom" SMSAs.

[20] In mapping the use of individual technologies, we also dropped all MSA/QMSAs with fewer than 20 observations to meet disclosure requirements and analytic criteria.

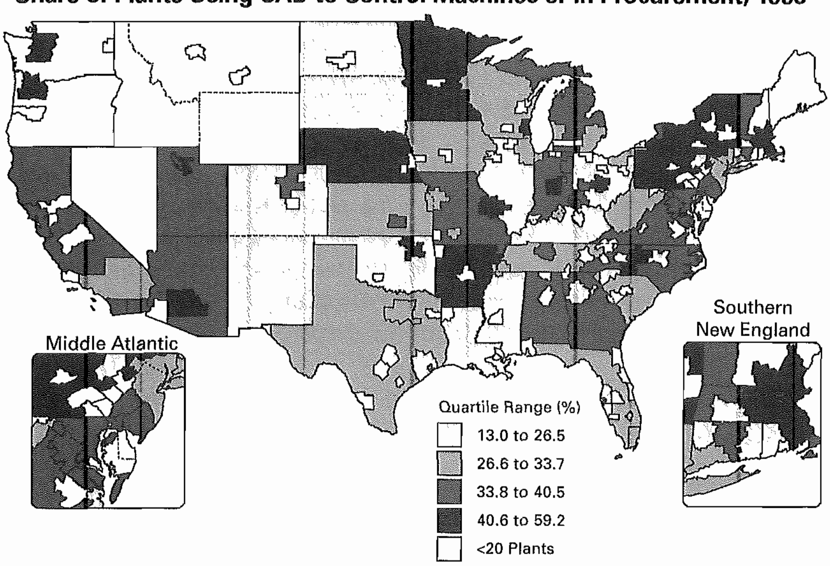
[21] It is important to note that the data displayed in the maps are weighted using SMT weights normalized by region-specific factors. See Appendix 2 for further discussion of the need to use weighted data and other weighting issues.

[22] Although the 1993 SMT does ask about the number of workstations involved—where that question is relevant—it provides no basis for comparing actual with potential use.

Map 6
Share of Plants Using CAD to Control Machines or in Procurement, 1988[a]



Map 7
Share of Plants Using CAD to Control Machines or in Procurement, 1993[a]



[a] Based on weighted data.
Note: Regions are MSAs and QMSAs, defined in the text.
Source: U.S. Bureau of the Census, Survey of Manufacturing Technology, 1988 and 1993.

Table 4
Technology Use, by Beale Code
Weighted Data

		Beale Code									
		Metro				Urban				Rural	
Item		0	1	2	3	4	5	6	7	8	9
Mean Number of Technologies	1988	3.0	3.0	3.2	3.2	3.3	4.2	3.1	3.1	2.4	2.6
	1993	3.5	3.9	3.6	3.9	3.9	4.1	4.1	3.7	3.0	3.7
Share of Establishments Using (%)											
At least five technologies	1988	25.1	24.6	28.0	27.1	31.8	41.3	25.9	26.0	15.3	19.1
	1993	31.0	37.0	32.3	35.2	35.4	45.3	40.4	36.0	32.1	38.0
CAD or CAE alone	1988	43.3	48.6	47.7	43.8	40.7	55.9	40.3	39.2	42.9	42.9
	1993	64.4	66.4	62.8	66.4	66.4	64.7	69.0	65.4	56.4	68.2
CAD used to control machines and/or in procurement	1988	19.0	14.4	21.2	17.0	12.9	23.1	16.7	15.4	14.5	9.3
	1993	35.8	41.4	31.3	31.5	32.7	37.7	30.8	25.7	26.7	41.2
LAN for factory use and/or intercompany computer networks	1988	26.2	27.4	27.9	30.3	32.8	39.9	35.3	34.6	25.7	26.5
	1993	33.2	40,8	35.7	37.4	30.3	42.5	40.2	38.1	25.8	38.6

Source: U.S. Bureau of the Census, Survey of Manufacturing Technology, 1988 and 1993.

between 1988 and 1993 was rapid and widespread; unusually intense technology use measured by 1988 criteria ranks only as lowest-quartile use by 1993. Nevertheless, the maps also indicate that the share of plants making above-average use of advanced technologies in any given period varies considerably across regions and within states. In 1988, relatively high-tech use within the SMT population was concentrated in parts of New York and New England, Virginia, South Carolina, Tennessee, Minnesota, Nebraska, and isolated metro regions dotted about the country. However, many metro areas, particularly in the East, appear as islands of relatively light technology use. By 1993 (Map 5), areas of intense technology use occur in parts of New York-New England, an arc of states that happen to be popular with foreign auto companies and their suppliers (Ohio, Illinois, Kentucky, and Tennessee), and a cluster formed by New Mexico, Colorado, and Nebraska. Some contiguous states in New England, the South Atlantic, the East North, and the West South Central regions also exhibit above-average adoption. On the whole, the pattern of technology use appears less scattered in 1993 than in 1988.

Maps 6 and 7 show the share of SMT establishments that had adopted a specific pair of relatively new technologies, CAD for controlling machines or for procurement. Again, these technologies spread rapidly in the sample period, with above-average use in 1988 subsumed into the lowest quartile by 1993. In the earlier period, the most intense use of CAD beyond design and engineering work occurred in a scattering of metro areas, including the Boston-Worcester-Lawrence and the Seattle-Tacoma-Bremerton CMSAs, as well as the southern Mountain states. By 1993, the heaviest use had spread through most of the Mid-Atlantic, along with Minnesota, Nebraska, and Arkansas. Again, metro regions (with more than 20 observations) do not appear to be at a disadvantage compared with surrounding areas. Interestingly, areas using large numbers of technologies in 1993 (Ohio, Kentucky, Tennessee, and Illinois, for instance) did not exhibit widespread adoption of these new CAD technologies, while West Coast areas, with low mean numbers, showed above-average use of extended CAD.

Because the maps (and, indeed, the construction of QMSAs) blur the distinctions between urban, suburban, and rural counties, Table 4 provides information similar to that covered by the maps for nine types of counties, running from urban core to rural as classified by the Beale codes.[23,24] For 1988 this table appears to confirm Harrison, Kelley, and Gant's (1996) conclusions that technology use peaks in urban counties outside of metropolitan areas (Beale Codes 4 and 5), at least for broad measures of technology use. The data suggest relatively limited technology use in core metro or completely rural areas. However, even in 1988, the pattern is less clear in the case of the newer CAD and LAN technologies. By 1993, moreover, the distinction between total technology use in metro and smaller urban counties seems less pronounced, possibly because the use of CAD and LAN technologies rose relatively fast in metro areas. This pattern raises a question as to whether new manufacturing technologies, which are comparatively inexpensive and reduce the relative cost of short production runs, may be particularly well-suited to the often small facilities located in metro areas.

Econometric Analysis of Technology Adoption

The maps just discussed suggest considerable variation in the use of technologies across and within states and regions. However, as discussed above, the maps are subject to several limitations, and we are reluctant to draw conclusions based solely on them. In order to investigate the

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[23] The 1993 urban-rural continuum codes, first developed in 1975 and updated by Calvin Beale, provide a classification scheme that distinguishes metropolitan counties by size and status as core or fringe counties and nonmetro counties by degree of urbanization and proximity to metro areas. These codes reflect population density, commuting patterns, and metro influence generally. See specific definitions in Appendix 4.

[24] Again, the data in the table are not adjusted for differences in industry mix or other determinants of technology adoption. In addition, outside of the metro areas, the number of observations falls off sharply.

regional aspects of technology diffusion more systematically, thus, we estimate a set of econometric models that allow us to control for the effects of plant, firm, and QMSA characteristics. Data for this exercise come from the 1988 and 1993 SMTs; details of our sample construction procedures, along with variable definitions and descriptive statistics, are provided in Appendix 4.

The first measure of technology adoption examined is the change in the number of advanced technologies used by SMT establishments between 1988 and 1993. For each of the 17 technologies covered by the SMT, establishments reported whether they had adopted the technology within the past two years, in the last two to five years, or more than five years ago. With this information, we can calculate the increase in the number of technologies used between 1988 and 1993 for each plant.[25]

As Figure 1 shows, a large share of the sample establishments either did not increase the number of technologies used, or added only one or two new technologies between 1988 and 1993. Accordingly, we have chosen a negative binomial specification for the conditional distribution of the change in the number of technologies used (since the negative binomial is appropriate for data concentrated at small, non-negative integer values).[26] In the negative binomial regression analysis, the natural logarithm of the expected increase in the number of technologies adopted is specified to be a linear function of various conditioning variables.

In our first specification, shown in the left-most column in Table 5, we control only for proximity to other users of advanced manufacturing technologies.[27] Our proximity measure is the natural logarithm of the mean number of advanced technologies used within the establishment's QMSA in 1988 (based on data from the 1988 SMT). Since large establishments seem likely to have a greater impact on neighbors' technology use than do small ones, we weighted each establishment by its total employ-

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[25] The count of technologies used in 1993 is based on a series of questions asking whether each technology is "currently used in operations," while the count of technologies used in 1988 is based on the questions asking whether each technology was used "more than 5 years ago." Less than 0.2 percent of our sample observations reported using more technologies in 1988 than in 1993. For these observations, the change in the number of technologies used variable was set equal to zero. In addition, establishments less than 5 years old (based on the answer to a question inquiring whether the establishment had been manufacturing products at the current location for "less than 5 years," "5 to 10 years," "16 to 30 years," or "over 30 years") were droppped from the sample, since they could not have adopted any technologies more than 5 years ago.

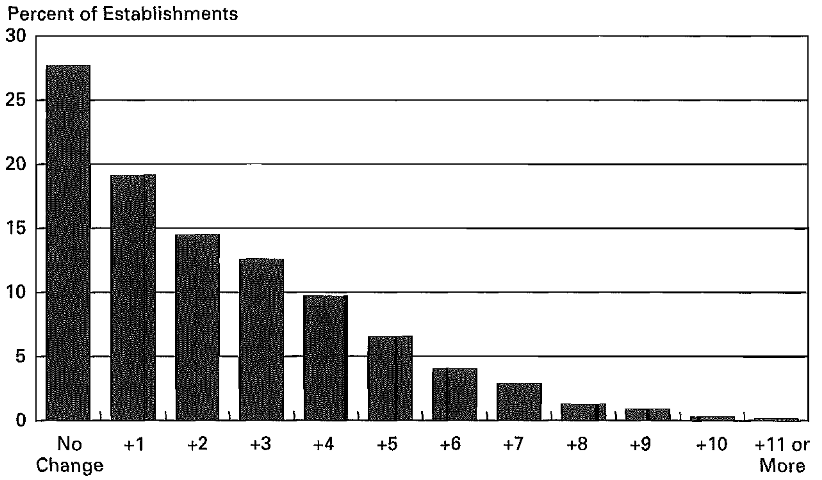
[26] Hausman, Hall, and Griliches (1984) and Cameron and Trivedi (1986) provide expositions of count data models, including the negative binomial regression specification.

The contributions to the log-likelihood function were weighted by the SMT sample weights in estimating the regressions.

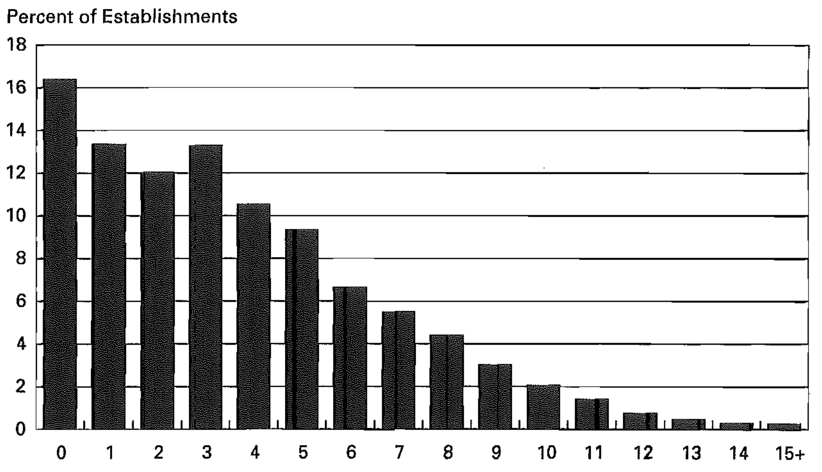
[27] The "ln(dispersion parameter)" coefficient indicates whether the dispersion in the count data is greater than would be expected under a Poisson data-generating process. The dispersion parameter would equal zero (and its natural log $-\infty$) in a Poisson specification.

Figure 1

Change in the Number of Technologies Used, 1988 to 1993



Number of Technologies Used, 1993



Source: Authors' calculations, using 1993 Survey of Manufacturing Technology.

Table 5
Results from Negative Binomial Regressions

	Change in Number of Technologies Used, 1988 to 1993			Number of Technologies Used, 1993		
Independent Variable	Coefficient (Std. Error)	Coefficient[a] (Std. Error)	Coefficient[a] (Std. Error)	Coefficient (Std. Error)	Coefficient[a] (Std. Error)	Coefficient[a] (Std. Error)
LN (PROXIMITY)	.226	.190	.105	.236	.182	.096
	(.051)	(.046)	(.051)	(.044)	(.035)	(.038)
LN (TECH USE_{88})		−.137	−.142			
		(.020)	(.020)			
MULTI-EST		.171	.131		.333	.301
		(.236)	(.236)		(.175)	(.174)
LN (EST SIZE)		.953	.942		.684	.680
		(.074)	(.074)		(.054)	(.054)
[LN (EST SIZE)]^2		−.061	−.060		−.033	−.033
		(.007)	(.007)		(.005)	(.005)
LN (FIRM SIZE)		−.036	−.028		−.088	.005
		(.063)	(.063)		(.047)	(.046)
[LN (FIRM SIZE)]^2		.004	.004		.008	.008
		(.004)	(.004)		(.003)	(.003)
MILITARY SPEC		.168	.163		.175	.171
		(.026)	(.026)		(.019)	(.019)
FABRICATION		.253	.257		.304	.304
		(.039)	(.039)		(.030)	(.030)
NO FABRIC/NO ASSM		−.299	−.296		−.206	−.202
		(.070)	(.070)		(.054)	(.054)
FOREIGN OWN		.123	.132		.114	.120
		(.042)	(.236)		(.031)	(.031)
AGE 16–30		−.111	−.112		−.068	−.068
		(.028)	(.028)		(.021)	(.021)
AGE >30		−.226	−.240		−.148	−.157
		(.031)	(.031)		(.023)	(.023)
HIGH SCHOOL+			1.875			1.597
			(.315)			(.237)
BA+			.449			.594
			(.370)			(.278)
RD_{1990}			−.022			.060
			(.075)			(.052)
$BEALE_{12}$			−.070			−.037
			(.032)			(.024)
$BEALE_{35}$			−.022			.013
			(.047)			(.035)
$BEALE_{69}$			−.043			−.019
			(.050)			(.037)
CONSTANT	.391	−.287	−3.781	.859	−2.027	−2.850
	(.097)	(.224)	(.282)	(.083)	(.167)	(.211)
ln (dispersion parameter)	−.402	−.995	−1.012	−.608	−1.676	−1.700
	(.035)	(.048)	(.048)	(.030)	(.053)	(.054)
Observations	6,214	6,214	6,214	6,214	6,214	6,214
Log Likelihood	−12,423	−11,706	−11,686	−14,861	−13,511	−13,485

[a]Indicates that specification also included 25 industry dummy variables. See Appendix 5 for criteria used for dropping observations. Source: Authors' calculations, using 1993 Survey of Manufacturing Technology.

ment in calculating the proximity measure.[28] The proximity coefficient can be interpreted as the elasticity of the expected change in technology use with respect to prior technology use by other firms in the same area. The elasticity is sizable, 0.23, and reasonably precisely estimated. Thus, the number of advanced technologies adopted by plants between 1988 and 1993 is estimated to be an increasing function of the level of technology use by nearby plants in the base year.

This estimate is consistent with proximity to other users of advanced technology being an important determinant of adoption, but this result could also be driven by more general agglomeration economies that lead similar firms (with similar needs for technology) to cluster geographically. To explore this hypothesis, we next added a set of establishment and firm characteristics to the model. Estimates from this specification are shown in the second column in Table 5; in addition to the variables shown, 25 industry dummy variables were also included in the estimation.[29]

Surprisingly, the inclusion of the establishment and firm characteristics has relatively little impact on the size of the estimated proximity effect. Apparently, in other words, the impact of proximity to high-tech neighbors on nearby plants' technology adoption decisions is not simply a matter of similar firms clustering together.

Turning to the establishment characteristics, the estimated coefficients on these variables generally conform with our expectations. The natural log of the number of technologies used by the firm in 1988 is negative and precisely estimated.[30] Firms that were already heavy users of technology tended to adopt comparatively few additional technologies, while firms that were less technologically intensive in 1988 most likely chose to adopt a greater number of new technologies in order to stay competitive.[31]

As in previous work, employment size is found to be an important predictor of technology adoption. The coefficient on the natural log of

[28] Some plants were included in both the 1988 and 1993 SMT samples; in addition, the parents of 1993 SMT establishments sometimes owned other plants within the same QMSA that were also included in the 1988 sample. To avoid having our proximity measure capture intra-firm or lagged plant effects, for each 1993 SMT establishment we calculated the proximity measure excluding other plants owned by the same firm (as of 1992) as well as the establishment itself. SMT sample weights (normalized to average 1 within each QMSA) were used in computing the proximity measure.

[29] The industry groups represented by the dummy variables were created by merging two or three similar 3-digit industries. Details are provided in the list of SIC groups in Appendix 4.

[30] Since a non-trivial number of establishments used none of the advanced technologies in 1988, one was added to the number of technologies used before taking logs.

[31] An alternative, more mechanical, explanation is that since the SMT only asked about 17 specific technologies, the higher the initial number of technologies, the smaller the maximum possible increase.

the employment size variable can be interpreted as the elasticity of the increase in the number of technologies used with respect to the number of employees. This elasticity is nearly 1 for small plants, but the negative coefficient on the quadratic term suggests that the elasticity decreases with plant size.

Why should we expect a positive relationship between technology adoption and employment size? Some explanations focus on there being a minimum plant scale associated with efficient utilization of given technologies. Other explanations relate to both firm and plant size. Economists have long pointed out, for instance, that large firms reap economies of scale in technology adoption because they can spread fixed costs, like the required R&D or the risk of failed implementation, over a larger sales base. While the expected returns to adoption are proportional to size, many of the costs are not. (See Babbage 1835, cited in Rosenberg 1994; Mansfield 1963; Keefe 1991; Nooteboom 1993; and Wozniak 1987, 1993.) In addition, large firms or plants may also encounter more frequent opportunities to make sometimes lumpy capital investments[32] (Rose and Joskow 1988) or to experiment. Large firms may also have relatively ready access to capital and a sophisticated R&D network.

In an attempt to sort out the relative importance of firm and plant size, we include firm employment as a measure of capital access and, possibly, R&D sophistication for multi-establishment firms.[33] Surprisingly, when we control for establishment employment, firm size appears to have relatively little effect on technology adoption. The indicator variable for multi-plant firms is positive but has a standard error more than twice its size.[34] The coefficients for the natural log of firm manufacturing employment and for the square of the log (both of which are interacted with the multi-plant dummy variable) are small and statistically insignificant. These results strongly suggest that plant size, rather than firm size, affects the speed of technology adoption.

As expected, the indicator variables for fabrication activity (FABRICATION) and defense-related production (MILITARY SPEC) are both positive and statistically significant, while the dummy variable indicating that a plant is engaged in neither assembly nor fabrication (NO

[32] While investment in CAD/CAM or LAN equipment might appear to be less lumpy than investment in flexible machining cells or automated materials handling systems, say, adoption of CAM or LAN systems requires developing a new system of organization and control, an expensive proposition, as Mowery (1988) points out.

[33] Our firm size variable captures only employment in establishments appearing in the 1992 Census of Manufactures. Employment in the non-manufacturing facilities belonging to parents of SMT establishments is not included in this measure.

[34] "Multi-plant" was defined to include firms with more than one plant appearing in the 1992 Census of Manufactures. Firms with a single manufacturing plant and other non-manufacturing facilities would not be classified as multi-plant by this definition.

FABRIC/NO ASSM) is negative and significant. Like production to military specification, foreign ownership (FOREIGN OWN) also has a significant positive association with technology use. This result is consistent with foreign direct investment theory linking investment activity with technological sophistication. By contrast, the coefficients on the plant age dummy variables suggest that older plants are slower to take up new technologies.

While the specification just discussed shows that the proximity effect remains largely intact after conditioning on plant characteristics, it does not address whether proximity is capturing spillover effects or is instead serving as a proxy for regional characteristics, like educational attainment, that facilitate technology adoption. We investigate this question in the third specification shown in Table 5, in which several QMSA characteristics are added to the model.

Although the size of the proximity elasticity drops to 0.105 when the QMSA variables are added to the model, it remains both economically and statistically significant. Among the QMSA variables added are two measures of the educational attainment of the labor force (the share of the adult population with a high school diploma but less than a B.A. and the share with a four-year college degree or more) since much previous research has documented a link between technology use and the education of the managers or workers at the facility with the new equipment or process. (See Bartel and Lichtenberg 1987; Doms, Dunne and Troske 1995; Nelson and Phelps 1966; and Wozniak 1987, 1993.) In addition, in the 1991 SMT, cost of education and training and lack of skilled labor were among the major impediments to technology adoption cited by respondents foreseeing barriers.[35]

The variable measuring the fraction of the adult population with a high school diploma but less than a B.A. (HIGH SCHOOL+) has a large, positive, and statistically highly significant coefficient. However, a similar variable measuring the share of the adult population with at least a four-year college degree (BA+) usually has a relatively small, positive, sometimes statistically significant coefficient. These combined results suggest that college graduates are associated with more technology adoption than high school dropouts but have a less favorable impact than high school graduates who did not complete a four-year college. We expected to find that access to a work force with at least a high school education would be associated with technology adoption, but we find the BA+ coefficient puzzling. One possible explanation is that

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[35] Somewhat less than half of the respondents anticipated barriers to acquiring equipment in any of the four technology groups covered. For those who foresaw difficulties, the top problems (out of 12 possibilities) were always cost of equipment and cost of software, generally followed by cost of training, lack of benefit, and lack of skilled work force.

manufacturers need educated workers but do not wish to pay production workers the college wage premium. Thus, the most attractive labor pool may contain a large share of individuals with a high school education or post-secondary technical training but not a four-year college degree. Or, professional workers may move in a national labor market. In addition, technologies could vary in their requirements for educated workers.[36] Finally, the BA+ variable may be picking up the effects of omitted QMSA characteristics like land prices and quality-adjusted labor costs.[37]

Because local firms benefit from proximity to research universities —by hiring graduates or faculty consultants, conducting joint research, attending seminars, and the like—the geographic variables also include university R&D spending per worker by QMSA (RD_{1990}).[38] Previous research has shown that proximity to major research universities has spillover effects in the case of patenting activity. Recently, moreover, many universities have strengthened their links to local industry through increased efforts to commercialize university inventions or through technology transfer programs. (See Bania, Eberts, and Fogarty 1993; Henderson, Jaffe, and Trajtenberg 1995.) However, as with the BA+ variable, our expectations were not borne out. The university R&D variable has a small, negative, statistically insignificant coefficient. While universities may have an important impact on generating new technologies, our results suggest that they have little to do with the diffusion of fairly mature technologies such as those measured by the SMT.

The last three geographic variables included in the specification are a set of dummy variables indicating whether the plant is located in a county assigned Beale codes 1 or 2 (non-core but large metro counties), 3 through 5 (small metro or large urban counties), or 6 through 9 (small urban and rural counties); the omitted category is Beale code 0 (central city counties of large metro areas). The Beale code dummy coefficients are all quite small and, with one exception, negative. This result reinforces the impression made by the simple tabulations shown in

[36] For instance, exceptions to the significant positive link between HIGH SCHOOL+ and adoption of specific technologies, discussed below, occur in the case of: 1) the relatively large-scale and little-used flexible manufacturing systems suitable for long production runs; 2) lasers, robots, and automated materials handling systems, also generally found in large-scale facilities in specific industries; and 3) the older programmable controllers now being replaced by more flexible CAD/CAM and LAN systems.

[37] Crude preliminary attempts at addressing this issue by adding measures of housing costs and average manufacturing earnings to the specification did not change the flavor of the results. An exploratory effort to control for variations in economic conditions across QMSAs, as measured by the change in manufacturing employment in the QMSA between 1987 and 1992, also had little perceptible impact on the results.

[38] The RD_{1990} variable is based on research and development expenditures of the top 280 research universities (ranked by R&D spending).

Table 4: Although the central urban counties may have lagged in technology adoption at one point, that effect is not apparent in the more recent data.

In addition to the regressions for change in number of technologies used, Table 5 also shows the results of estimating negative binomial regressions where the dependent variable is the number of advanced technologies used in 1993 (with identical conditioning variables, excluding the number of technologies used in 1988). The results are very similar to those discussed earlier, an outcome suggesting that technology adoption occurred via a similar process both before 1988 and between 1988 and 1993.[39]

While a count of the number of technologies used is a useful scalar measure of technology intensity, we were also interested in examining the diffusion of specific technologies. For this purpose, we grouped the 17 technologies covered by the SMT into 10 relatively homogeneous categories. For each category, we formed an ordinal variable measuring the speed of technology adoption. This variable takes on the highest value if the plant adopted the technology more than five years ago, and the lowest value if the establishment had not yet adopted the technology (as of 1993).[40]

For each of the 10 technology groups, we estimated an ordered probit regression relating the ordinal speed of technology adoption to the same set of variables used in the technology count analysis already discussed. But proximity is now measured as the fraction of SMT employment within the QMSA using the technology in question in 1988.[41] As before, we first condition on proximity alone, then add establishment characteristics, and finally include QMSA variables. Estimation results are shown in Table 6; to conserve space, the establishment characteristic coefficients are not shown in the text (but are presented in Appendix 6).

When we control only for proximity, once again the proximity effect is sizable and nearly always statistically significant. In these regressions the dependent variables are latent measures of the speed of technology adoption, normalized to have unit variance. Thus, the proximity coefficient of 0.46 for the first technology group (computer-aided design or engineering), for example, can be interpreted as indicating that if CAD

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[39] In a future revision of this paper, we will address this hypothesis more directly by estimating regressions with the number of technologies used in 1988 specified as the dependent variable.

[40] The two intermediate categories are: adopted two to five years ago, and adopted within the past two years—again relative to 1993. For each technology group, the technology was considered "adopted" at the earliest time any component technology was used.

[41] The proximity measure was calculated using steps similar to those described for the proximity variable used in the negative binomial regressions, as described above in the text and in footnote 28. Again, they are subject to the same limitation, being based only on plants observed in the 1988 SMT.

Table 6
Technology Adoption Estimation Results
Ordered Probit Specification

	Technology Groups									
Variable	1	2	3	4	5	6	7	8	9	10
	Controlling Only for Proximity									
PROXIMITY	.460	.478	.537	.247	.430	.417	.390	.500	.705	.403
	(.129)	(.105)	(.128)	(.140)	(.124)	(.125)	(.109)	(.111)	(.126)	(.131)
	Controlling for Proximity and Establishment Characteristics[a]									
PROXIMITY	.396	.408	.297	.183	.361	.229	.339	.428	.377	.373
	(.134)	(.111)	(.138)	(.150)	(.141)	(.137)	(.114)	(.116)	(.134)	(.137)
	Controlling for Proximity, QMSA Characteristics, and Establishment Characteristics[a]									
PROXIMITY	−.097	.093	.140	.196	.358	.150	.080	.247	.287	.250
	(.167)	(.129)	(.146)	(.155)	(.149)	(.147)	(.130)	(.123)	(.140)	(.143)
HIGH SCHOOL+	1.821	1.604	1.122	.616	.688	1.583	2.696	2.366	.314	1.272
	(.403)	(.432)	(.409)	(.519)	(.536)	(.507)	(.430)	(.427)	(.430)	(.433)
BA+	−.111	1.499	1.702	−.016	−.361	.135	1.289	−.265	−.973	1.353
	(.513)	(.511)	(.481)	(.630)	(.640)	(.608)	(.535)	(.490)	(.504)	(.512)
RD_{1990}	.148	.029	−.006	−.014	−.183	.161	.255	.127	.215	.011
	(.089)	(.100)	(.099)	(.124)	(.150)	(.113)	(.092)	(.094)	(.097)	(.098)
$BEALE_{12}$	.007	−.037	−.042	.044	−.082	−.060	−.017	−.018	−.006	−.011
	(.039)	(.043)	(.042)	(.055)	(.056)	(.052)	(.044)	(.043)	(.045)	(.045)
$BEALE_{35}$	.068	−.040	.028	.192	−.008	−.002	.043	−.135	−.030	.065
	(.058)	(.065)	(.064)	(.080)	(.082)	(.078)	(.065)	(.064)	(.066)	(.067)
$BEALE_{69}$	.024	−.110	−.046	.066	−.002	−.034	−.063	−.038	.030	.141
	(.061)	(.068)	(.067)	(.086)	(.085)	(.082)	(.070)	(.067)	(.070)	(.070)
CUTOFF POINT 1	3.778	3.667	4.610	2.951	3.768	2.859	4.392	3.873	2.448	3.773
	(.355)	(.398)	(.393)	(.481)	(.504)	(.465)	(.404)	(.389)	(.403)	(.405)
CUTOFF POINT 2	4.176	3.942	4.769	3.183	3.989	3.067	4.795	4.317	2.636	4.049
	(.356)	(.399)	(.394)	(.482)	(.504)	(.465)	(.404)	(.389)	(.403)	(.405)
CUTOFF POINT 3	5.099	4.578	5.175	3.637	4.380	3.470	5.515	4.956	3.100	4.584
	(.357)	(.399)	(.394)	(.482)	(.504)	(.465)	(.405)	(.390)	(.404)	(.406)
Observations	6165	6177	6141	6182	6165	6171	6121	6119	6095	6115

Technology Groups

1 CAD or CAE alone
2 CAD used to control machines or in procurement
3 NC/CNC
4 Flexible manufacturing cells or systems
5 Materials working lasers, robots, and automated materials handling equipment
6 Sensor-based inspection/testing
7 LAN for technical data
8 LAN for factory use and intercompany computer networks
9 Programmable controllers
10 Computers used to control the factory floor

See Appendix 5 for criteria used for dropping observations.

[a]Coefficients for establishment characteristics are shown in Appendix 6.

Source: Authors' calculations, using 1993 Survey of Manufacturing Technology.

or CAE technology had been used by an extra 10 percent of a QMSA's work force, the latent technology index would have been roughly 0.05 standard deviations higher.[42] The proximity effects generally seem closer in magnitude to each other than one would expect a priori; eight out of the 10 coefficients have values between 0.35 and 0.55.

When plant and firm characteristics are added to the specification, the proximity coefficients tend to drop by a somewhat greater percentage than in the count regressions. This result probably reflects the fact that industry specificity is greater for use of particular technologies than for the number of technologies used. Overall, however, proximity to other users of the same technology remains important even when plant characteristics are taken into account.

The addition of geographic characteristics changes the picture considerably. The value of several of the proximity coefficients drops a good deal, and most (taken individually) are now statistically insignificant. The educational attainment coefficients also vary a good deal in magnitude, although the share of the adult population who had graduated from high school generally emerges as an important determinant of the speed of technology adoption. The R&D and Beale code coefficients are erratic, varying in both magnitude and sign over the technology groups.

Why are the results so much weaker when we examine the effects of proximity and other geographic characteristics on the adoption of individual technologies, rather than on the total number of technologies used? One possibility is that, beyond the impact of proximity to users of a specific technology, proximity to technologically advanced plants in general has an independent effect on technology adoption. This omitted variable may be biasing the coefficients of the other local area variables in ways that vary over the technology groups. Another possibility is that each ordinal variable is too crude an indicator of the speed of technology adoption to permit us to decipher the separate influences of the geographic variables. Finally, it may be the case that, in truth, the proximity and other geographic characteristics affect technology adoption in ways

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[42] A somewhat more down to earth interpretation can be made by examining the estimated cutoff points shown in the Appendix. The cutoff points show how the ordinal variable categories are mapped into ranges of the latent (unit variance) speed of adoption variable. The first cutoff point divides the "have not adopted" and "adopted within the past two years" categories; the second cutoff point divides the "adopted within the past two years" and "adopted two to five years ago" categories; the third cutoff point divides the "adopted two to five years ago" and "adopted more than five years ago" categories.

that vary widely over technology groups. Further research is needed to explore these possibilities.[43]

CONCLUSIONS

Geography does make a difference to the speed of adoption of advanced technologies. Proximity to other users of technology is associated with higher rates of adoption, and this effect remains apparent even when industry and other plant characteristics are taken into account. In many ways, this outcome is surprising. Given the well-developed communications and transportation networks, and national markets for capital goods and skilled workers, one might expect the United States to approach the limiting case of immediate, costless diffusion of technology.

Human capital appears to be an important component of the proximity effect. Access to a work force with at least a high school

[43] In his thoughtful comments on this paper at the June conference, John Haltiwanger emphasized the drawbacks of using retrospective data to measure the change in the number of technologies used between 1988 and 1993 (in the negative binomial regressions) and the timing of technology adoption (in the ordered probits). As Haltiwanger pointed out, comparing responses given in 1988 and 1993 for establishments in both the 1988 and 1993 SMT reveals a large number of inconsistencies.

In response to these comments, we reran all of our regressions using data from the 1988 and 1993 SMTs for 2,228 establishments appearing in both surveys. Using current 1988 and 1993 responses rather than retrospective information for this relatively small sample does not change the overall flavor of the results. If anything—to our surprise—this change strengthens the conclusion that proximity to early users encourages technology adoption. Results for the regressions estimating the change in the number of technologies used for the matched subsample reveal that the size of the proximity coefficient is nearly twice as large when the 1988 SMT information is used as when only the retrospective information from the 1993 SMT is used. However, in the case of the ordered probits, the differences between the results based on the 1988 SMT information and the results based solely on the 1993 retrospective data are less clear.

We note one interesting difference between the full sample results shown in Table 5 and the results for the same specifications estimated using the subsample of plants found in both the 1988 and 1993 SMTs. In the subsample, the size of the proximity coefficient is much larger when establishment characteristics are held constant than when proximity is the only explanatory variable. This difference holds whether the dependent variable is based only on retrospective information or on information from the matched 1988 and 1993 SMT observations. The proximity coefficient drops somewhat when the geographic characteristics are added to the set of explanatory variables, but the drop is much smaller than occurs with the full sample. A likely reason for the differences between the results for the full and subsamples is that the matched 1988-93 subsample contains relatively large firms. Since the distribution of plant characteristics differs markedly between the full sample and the subsample, it is not surprising that adding plant characteristics to the specification has quite different effects on the magnitude of the proximity coefficients estimated from the two samples.

The authors would be glad to supply regression results for the matched 1988–93 subsample upon request.

education is associated with a faster rate of technology adoption, and some, perhaps much, of the remaining proximity effect likely reflects technical knowledge spread through social interactions within geographic areas. In other words, human capital seemingly influences not just the productivity with which a given stock of physical capital is used, but also the technology incorporated in that capital stock.

To summarize more specific results, the regression analysis generally confirms previous research linking technology adoption to establishment size; however, it finds little association between multi-establishment firm size or multi-establishment status and technology use. The limited impact of firm size suggests that the positive link between size and technology use reflects plant scale rather than favored access to capital or firm-level technological sophistication. The research also reconfirms that facilities that engage in fabrication use relatively large numbers of technologies.[44] By contrast, unlike previous studies, this paper also finds some evidence of a significant negative relationship between plant age and technology adoption. As expected, moreover, manufacturing to military specification has a sizable and consistently positive impact on technology adoption, a finding that demonstrates yet again how defense spending serves as this country's industrial policy. Foreign ownership also has a positive association with technological sophistication. Finally, this research finds almost no evidence that, in 1993, center-city counties of large metro areas were at a significant disadvantage in terms of technology use compared with smaller or less urban areas. Indeed, if anything, the data suggest a positive association between a core urban location and the increase in the number of technologies used between 1988 and 1993.[45] Possibly, in other words, the new CAM and LAN technologies are especially suited to urban manufacturing needs.

As for the geographic characteristics, although we were not able to disentangle proximity/spillover effects from the impact of educational attainment/university R&D in a satisfactory manner, we generally find a significant link between technology adoption and the availability of a relatively well-educated work force, particularly in the case of the newer CAD and LAN technologies. However, the relatively great importance of high school graduates as compared with individuals with college degrees remains puzzling. Nevertheless, we believe we see enough evidence of uneven technology diffusion, particularly of the newer technologies, to warrant further research on this topic. Exploring the impact of other locational variables that may be more directly linked to technology adoption—the availability of engineers and technicians or

[44] The association is less pronounced in the case of the CAD and LAN technologies.
[45] Including, in particular, LAN for factory use and intercompany networks.

software designers, for example, or proximity to leading vendors of high-tech equipment—might be a promising approach. In addition, we need to develop a more complex model of the endogenous relationships between proximity and location and between investment and technology adoption.

In sum, the results of this first effort to explore the geographic dimensions of the SMT suggest that locational characteristics do play a role in technology diffusion. Because the repetitive process of technology adoption is extremely expensive for individual firms and the nation, gaining a better understanding of this process remains an important goal.

Appendix 1—Description of Manufacturing Technologies, Taken from "Manufacturing Technology: Prevalence and Plans for Use 1993"

1. Design and Engineering

a. **Computer Aided Design (CAD) and/or Computer Aided Engineering (CAE)**—Use of computers for drawing and designing parts or products and for analysis and testing of designated parts or products.

b. **Computer Aided Design (CAD)/Computer Aided Manufacturing (CAM)**—Use of CAD output for controlling machines used to manufacture the part or product.

c. **Digital Data Representation**—Use of digital representation of CAD output for controlling machines used in procurement activities.

2. Fabrication/Machining and Assembly

a. **Flexible Manufacturing Cells (FMC)**—Two or more machines with automated material handling capabilities controlled by computers or programmable controllers, capable of single-path acceptance of raw material and single-path delivery of finished product.

Flexible Manufacturing Systems (FMS)—Two or more machines with automated material handling capabilities controlled by computers or programmable controllers, capable of multiple-path delivery of finished product. An FMS also may be comprised of two or more FMCs linked in series or parallel.

b. **NC/CMC Machines**—A single machine either numerically controlled (NC) or computer numerically controlled (CNC) with or without automated material handling capabilities. NC machines are controlled by numerical commands punched on paper or plastic mylar tape. CNC machines are controlled electronically through a computer residing in the machine.

c. **Materials Working Laser(s)**—Laser technology used for welding, cutting, treating, scribing, and marking.

d. **Pick and Place Robot(s)**—A simple robot, with one, two, or three degrees of freedom, which transfers items from place to place by means of point-to-point moves. Little or no trajectory control is available.

e. **Robot(s)**—A reprogrammable, multifunctional manipulator designed to move materials, parts, tools, or specialized device through variable programmed motions for the performance of a variety of tasks.

3. Automated Material Handling

a. **Automatic Storage and Retrieval System (AS/RS)**—Computer-controlled equipment providing for the automatic handling and storage of materials, parts, subassemblies, or finished products.

b. **Automatic Guided Vehicle Systems (AGVS)**—Vehicles equipped with automatic guidance devices programmed to follow a path that interfaces with work stations for automated or manual loading and unloading of materials, tools, parts, or products.

4. Automated Sensor Based Inspection and/or Testing Equipment

Automated Sensor Based Inspection and/or Testing Equipment—Includes automated technical data within design and engineering departments.

5. Communications and Control

a. **Technical Data Network**—Use of local area network (LAN) technology to exchange technical data within design and engineering departments.

b. **Factory Network**—Use of local area network (LAN) technology to link subcontractors, suppliers, and/or customers with the plant.

c. **Intercompany Computer Network**—Use of network technology to link subcontractors, suppliers, and/or customers with the plant.

d. **Programmable Controller(s)**—A solid state industrial control device that has programmable memory for storage of instructions, which performs functions equivalent to relay panel or wired solid state logic control system.

e. **Computer(s) Used for Control on the Factory Floor**—Excludes computers imbedded within machines, or computers used solely for data acquisitions or monitoring. Includes computers that may be dedicated to control but are capable of being programmed for other functions.

Appendix 2— Use of SMT Sample Weights in Constructing Geographic Estimates

To understand the importance of using weighted data for geographic analysis, suppose that a region has a disproportionately large share of big firms, which have a relatively high probability of both sample inclusion and advanced technology use. While unweighted data would tend to exaggerate the extent of technology adoption in that area, weighted data (normalized by region-specific factors) will not be subject to that bias since the weights correct for differences in probability of sample inclusion across strata.

Regionally normalized sample weights are appropriate for our purposes because they result in unbiased estimates of means and proportions within regions. Suppose, for example, that N and n are the overall population and sample sizes, that N_h and n_h are the population and sample sizes in stratum h, and that N_g and n_g are the population and sample sizes in geographic area g. Thus, N_{gh} and n_{gh} are the population and sample sizes of establishments in both stratum g and area h. The sample weight for establishments in the SMT is N_h / n_h, the inverse of the sampling probability. A standard result in sampling theory is that sample means and proportions computed using these weights, multiplied by n/N to normalize to one, will be unbiased estimators of their population counterparts (Cochran 1963, chapter 5). In other words, the arithmetic mean of $(n/N)(N_h/n_h)y_i$ will be an unbiased estimator of the population mean of y.

Within geographic area g, the appropriate sample weight to use in estimating population means and proportions is N_{gh}/n_{gh} normalized to average one within region g. However, simple random sampling within strata leads to the result that $N_{gh}/n_{gh} = N_h/n_h$. In other words, since the probability of sample inclusion within a given stratum does not vary over regions, the sample weight for an establishment in stratum i relative to the sample weight of an establishment in stratum j should also not vary over regions.

The normalization factor for region g is n_g/N_g. This factor, the probability of sample selection in region g (not conditioning on stratum membership) will vary over regions because of interregional differences in industry mix and the distribution of employment size. Thus, region-specific normalization factors must be applied in computing estimates by region. The normalization factors can be simply calculated as the multiplicative scalar factors which result in the weights having mean values equal to one within each region. They do not need to be estimated using an external data source.

Appendix 3—Distribution of Observations by CMSA, 1993

Number of Observations	Number of QMSAs	Cumulative Observations	Total Share of Observations
6–7	12	76	1.07
8–10	15	214	3.01
11–15	29	596	8.38
16–20	14	843	11.85
21–25	12	1112	15.63
26–30	7	1310	18.41
31–35	2	1376	19.34
36–40	10	1754	24.65
41–45	6	2016	28.33
46–50	5	2256	31.71
51–55	7	2629	36.95
56–60	6	2978	41.86
61–65	1	3043	42.77
66–70	3	3251	45.69
70–75	6	3689	51.85
76–100	5	4117	57.86
101–125	4	4578	64.34
126–150	2	4844	68.08
151–200	2	5166	72.61
201–250	3	5857	82.32
251–400	2	6558	92.17
Over 400	1	7115	100.00

Source: U.S. Bureau of the Census, Survey of Manufacturing Technology, 1993.

APPENDIX 4—VARIABLE DEFINITIONS AND DATA SOURCES

Variable	Description	Source and Comments
Dependent:		
TECH NUM_{93}	Number of technologies used by establishment in 1993, used in negative binomial regressions	Survey of Manufacturing Technology (SMT) 1993, extract provided by the U.S. Bureau of the Census, Center for Economic Studies (CES)
Δ TECH $NUM_{88\text{-}93}$	Change in number of technologies used by establishment 1988–93, used in negative binomial regressions	SMT 1993, extract provided by the CES. (SMT 1988 used in regressions described in footnote 43.)
$PROB(TECH_t)$	Probability of establishment adopting $technology_t$: not yet, less than 2 years ago, 2 to 5 years ago, or more than 5 years ago, for technology groups 1–10, used in ordered probit regressions	SMT 1993, extract provided by the CES. (SMT 1988 used in regressions described in footnote 43.)
Independent:	Establishment Characteristics:	
LN (TECH USE_{88})	Natural log of number of technologies used by establishment in 1988, used in regression for Δ tech $num_{88\text{-}93}$	SMT 1993, extract provided by the CES. (SMT 1988 used in regressions described in footnote 43.)
LN (EST SIZE) $[\text{LN (EST SIZE)}]^2$	Establishment size: natural log and natural log squared of total employment at establishment in 1992	Census of Manufactures (CM) 1992, extract from the Longitudinal Research Database (LRD) provided by the CES
LN (FIRM SIZE) $[\text{LN (FIRM SIZE)}]^2$	Firm size: natural log and natural log squared of total 1992 employment at firm to which establishment belongs, for multi-establishment firms	CM 1992, extract from the LRD provided by the CES
AGE 16–30 AGE >30	Dummies for age of establishment: ages 16 to 30 and above 30 versus ages 6 to 15	CM 1992, extract from the LRD provided by the CES
$IND_2 \ldots IND_{25}$	Dummies for 3-digit SIC cluster; see list below	SMT 1993, extract provided by the CES
MULTI-EST	Dummy for multi-establishment firm in 1992	CM 1992, extract from the LRD provided by the CES
MILITARY SPEC	Dummy: establishment produces some goods to military specification: yes versus no or don't know	SMT 1993, extract provided by the CES
FABRICATION NO FABRIC/ NO ASSM	Dummy for type of operation: fabrication or fabrication and assembly versus assembly only and neither versus assembly only	SMT 1993, extract provided by the CES

Appendix 4—continued

Variable	Description	Source and Comments
FOREIGN OWN	Dummy for foreign owned: yes versus no or don't know	SMT 1993, extract provided by the CES
	Location Characteristics:	
PROXIMITY	Proximity to other users of SMT technologies: natural log of mean number of technologies used in QMSA by unrelated establishments in 1988, weighted by plant employment, in the negative binomial regressions; share of SMT employment in QMSA at unrelated establishments using the same technology$_t$ in 1988, in the ordered probits	SMT 1988 and 1993, extract provided by CES
HIGH SCHOOL+	Share of the population 25 years of age and over with a high school diploma but less than a B.A., 1990, in QMSA	U.S. Bureau of the Census, *County and City Data Book*, 1994
BA+	Share of the population 25 years of age and over with a bachelor's degree and above, 1990, in QMSA	U.S. Bureau of the Census, *County and City Data Book, 1994*
RD_{90}	Academic science and engineering R&D expenditures by top 280 research universities, per worker, in QMSA, in FY 1993	National Science Foundation/SRS, Survey of Scientific and Engineering Expenditures at Universities and Colleges
$BEALE_{12}$ . . . $BEALE_{69}$	Dummies for Beale codes, 1993: 1 and 2; 3, 4, 5; and 6, 7, 8, 9 versus 0	Butler and Beale, U.S. Department of Agriculture, Economic Research Service, 1993

SIC Groups

34 Fabricated Metal Products

341 + 343	Metal cans and shipping containers + plumbing and heating except electric
342	Cutlery, handtools, and hardware
344	Fabricated structural metal products
345 + 346	Screw machine products, bolts, etc. + metal forgings and stampings
347 + 349	Metal services, nec + miscellaneous fabricated metal products
348	Ordnance and accessories

35 Industrial Machinery and Equipment

351	Engines and turbines
352 + 353	Farm and garden machinery + construction and related
354	Metalworking machinery
355 + 358	Special industry machinery + refrigeration and service machinery
356 + 359	General industry machinery + industrial machinery, nec
357	Computers and office equipment

Appendix 4—continued

36 Electronic and Other Electric Equipment

361 + 362	Electric distribution equipment + electrical industrial apparatus
363 + 364 + 365 + 369	Household appliances + electric lighting and wiring + household audio and video equipment + miscellaneous
366	Communications equipment
367	Electronic components and accessories

37 Transportation Equipment

371	Motor vehicles and equipment
372	Aircraft and parts
373	Shipbuilding, boats and repair
376	Guided missiles
374 + 375 + 379	Railroad equipment + motorcycles, bicycles, and parts + miscellaneous

38 Instruments and Related Products

381	Search and navigation
382	Measuring and controlling devices
384	Medical instruments and supplies
385 + 386 + 387	Ophthalmic goods + photographic equipment and supplies + watches and clocks

Technology Groups

1 CAD or CAE alone
2 CAD used to control machines or in procurement
3 NC/CNC
4 Flexible manufacturing cells or systems
5 Materials working lasers, robots, and automated materials handling equipment
6 Sensor-based inspection/testing
7 LAN for technical data
8 LAN for factory use and intercompany computer networks
9 Programmable controllers
10 Computers used to control the factory floor

Rural–Urban Continuum Codes for Metro and Nonmetro Counties (Beale Codes)

Metro Counties

0 Central counties of metro areas of 1 million population or more
1 Fringe counties of metro areas of population of 1 million or more
2 Counties in metro areas of 250,000 to 1 million population
3 Counties in metro areas of fewer than 250,000 population

Nonmetro Counties

4 Urban population of 20,000 or more, adjacent to a metro area
5 Urban population of 20,000 or more, not adjacent to a metro area
6 Urban population of 2,500 to 19,999, adjacent to a metro area
7 Urban population of 2,500 to 19,999, not adjacent to a metro area
8 Completely rural or less than 2,500 urban population, adjacent to a metro area
9 Completely rural or less than 2,500 urban population, not adjacent to a metro area

Appendix 4—continued

Descriptive Statistics for Variables

Variable	Mean	Standard Deviation
TECH NUM_{93}	3.686	3.116
Δ TECH NUM_{93}	2.267	2.245
LN (TECH USE_{88})	1.420	1.976
LN (EST SIZE)	4.282	1.070
$[\text{LN (EST SIZE)}]^2$	19.485	10.494
LN (FIRM SIZE)[a]	7.352	2.036
$[\text{LN (FIRM SIZE)}]^{2a}$	58.199	31.475
AGE 16–30	.330	
AGE >30	.275	
MULTI-EST	.397	
MILITARY SPEC	.382	
FABRICATION	.796	
NO FABRIC/NO ASSM	.061	
FOREIGN OWN	.079	
PROXIMITY	6.794	1.724
PROX1	.727	.108
PROX2	.442	.147
PROX3	.661	.118
PROX4	.320	.138
PROX5	.514	.150
PROX6	.428	.149
PROX7	.483	.146
PROX8	.556	.140
PROX9	.667	.128
PROX10	.603	.125
HIGH SCHOOL+	.554	.044
BA+	.203	.054
RD_{1990}	.131	.185
$BEALE_{12}$	.251	
$BEALE_{35}$	.126	
$BEALE_{69}$	.116	
Observations	6214	

[a]These variables are reported only for establishments that are part of a multi-establishment firm; therefore, the number of observations for these variables is 3482.

Source: Survey of Manufacturing Technology, 1988 and 1993.

Appendix 5—Criteria for Dropping Observations from Analysis

Criteria for dropping observations include:

1. Establishment shipments valued at less than $1,000
2. Establishment employment of less than 10 for production workers or total employees
3. Observations coded AR (administrative record) in 1988, for which data were fully imputed
4. Establishments lacking unique permanent plant numbers (an issue in 1993 only)
5. Establishments with inconsistent geographic codes
6. Multi-establishment plants without an identifiable parent firm in 1992
7. Establishments with illogical or out-of-range survey responses
8. Establishments less than six years old (for the regression analysis)
9. Establishments in Alaska and Hawaii

Appendix 6—Technology Adoption Estimation Results

Technology Adoption Estimation Results: Ordered Probit Specification

	Technology Group 1			Technology Group 2		
Independent Variable	Coefficient (Std. Error)	Coefficient (Std. Error)	Coefficient (Std. Error)	Coefficient (Std. Error)	Coefficient (Std. Error)	Coefficient (Std. Error)
PROXIMITY	.460 (.129)	.396 (.134)	−.097 (.167)	.478 (.105)	.408 (.111)	.093 (.129)
MULTI-EST		.454 (.295)	.443 (.296)		.194 (.325)	.095 (.327)
LN (EST SIZE)		.563 (.101)	.567 (.101)		.183 (.103)	.206 (.104)
[LN (EST SIZE)]^2		−.014 (.011)	−.015 (.011)		.011 (.011)	.009 (.011)
LN (FIRM SIZE)		−.099 (.081)	−.098 (.081)		−.066 (.088)	−.041 (.089)
[LN (FIRM SIZE)]^2		.007 (.005)	.007 (.005)		.004 (.006)	.003 (.006)
MILITARY SPEC		.140 (.031)	.131 (.032)		.241 (.034)	.227 (.035)
FABRICATION		.104 (.047)	.107 (.047)		.460 (.056)	.465 (.056)
NO FABRIC/ NO ASSM		−.645 (.083)	−.642 (.083)		−.166 (.103)	−.167 (.103)
FOREIGN OWN		.052 (.055)	.056 (.055)		.019 (.060)	.022 (.061)
AGE 16–30		.012 (.034)	.013 (.035)		.003 (.038)	.004 (.039)
AGE >30		−.111 (.038)	−.118 (.038)		−.040 (.042)	−.053 (.042)
HIGH SCHOOL+			1.821 (.403)			1.604 (.432)
BA+			1.707 (.466)			1.499 (.511)
RD_{1990}			.148 (.089)			.029 (.100)
$BEALE_{12}$			.001 (.039)			−.037 (.043)
$BEALE_{35}$			.068 (.058)			−.040 (.065)
$BEALE_{69}$			.024 (.061)			−.110 (.068)
CUTOFF POINT 1	−.042 (.095)	2.751 (.284)	3.778 (.355)	.605 (.050)	2.586 (.298)	3.667 (.398)
CUTOFF POINT 2	.290 (.095)	3.147 (.285)	4.176 (.356)	.849 (.050)	2.860 (.298)	3.942 (.399)
CUTOFF POINT 3	1.082 (.096)	4.067 (.286)	5.099 (.357)	1.421 (.052)	3.494 (.298)	4.578 (.399)
Observations	6165	6165	6165	6177	6177	6177
Log Likelihood	−8177	−7371	−7354	−6280	−5821	−5807

Source: Authors' calculations, using 1993 Survey of Manufacturing Technology.

Appendix 6 (cont'd)
Technology Adoption Estimation Results: Ordered Probit Specification

	Technology Group 3			Technology Group 4		
Independent Variable	Coefficient (Std. Error)	Coefficient (Std. Error)	Coefficient (Std. Error)	Coefficient (Std. Error)	Coefficient (Std. Error)	Coefficient (Std. Error)
PROXIMITY	.537 (.128)	.297 (.138)	.140 (.146)	.247 (.140)	.183 (.150)	.196 (.155)
MULTI-EST		.427 (.320)	.367 (.322)		−.469 (.421)	−.442 (.422)
LN (EST SIZE)		.441 (.107)	.469 (.107)		.289 (.124)	.261 (.125)
[LN (EST SIZE)]^2		−.013 (.011)	−.016 (.011)		.004 (.012)	.006 (.012)
LN (FIRM SIZE)		−.131 (.088)	−.118 (.089)		.102 (.110)	.093 (.110)
[LN (FIRM SIZE)]^2		.009 (.006)	.008 (.006)		−.003 (.007)	−.002 (.007)
MILITARY SPEC		.270 (.034)	.256 (.035)		.173 (.044)	.182 (.044)
FABRICATION		1.221 (.059)	1.228 (.060)		.154 (.067)	.149 (.067)
NO FABRIC/ NO ASSM		.150 (.099)	.143 (.099)		−.347 (.132)	−.349 (.133)
FOREIGN OWN		.067 (.061)	.069 (.061)		.073 (.070)	.077 (.070)
AGE 16–30		−.033 (.038)	−.028 (.038)		−.107 (.050)	−.116 (.050)
AGE >30		−.003 (.041)	−.006 (.041)		−.142 (.054)	−.152 (.054)
HIGH SCHOOL+			1.122 (.409)			.616 (.519)
BA+			1.702 (.481)			−.016 (.630)
RD_{1990}			−.006 (.099)			−.014 (.124)
$BEALE_{12}$			−.042 (.042)			.044 (.055)
$BEALE_{35}$			.028 (.064)			.192 (.080)
$BEALE_{69}$			−.046 (.067)			.066 (.086)
CUTOFF POINT 1	.262 (.086)	3.666 (.306)	4.610 (.393)	1.157 (.049)	2.642 (.351)	2.951 (.481)
CUTOFF POINT 2	.384 (.086)	3.824 (.306)	4.769 (.394)	1.359 (.050)	2.873 (.351)	3.183 (.482)
CUTOFF POINT 3	.711 (.086)	4.228 (.307)	5.175 (.394)	1.761 (.053)	3.326 (.352)	3.637 (.482)
Observations	6141	6141	6141	6182	6182	6182
Log Likelihood	−6954	−5997	−5982	−3457	−3128	−3121

Source: Authors' calculations, using 1993 Survey of Manufacturing Technology.

Appendix 6 (cont'd)
Technology Adoption Estimation Results: Ordered Probit Specification

	Technology Group 5			Technology Group 6		
Independent Variable	Coefficient (Std. Error)	Coefficient (Std. Error)	Coefficient (Std. Error)	Coefficient (Std. Error)	Coefficient (Std. Error)	Coefficient (Std. Error)
PROXIMITY	.430 (.124)	.361 (.141)	.358 (.149)	.417 (.125)	.229 (.137)	.150 (.147)
MULTI-EST		.630 (.431)	.655 (.431)		.143 (.391)	.124 (.392)
LN (EST SIZE)		.355 (.137)	.335 (.137)		.068 (.121)	.057 (.122)
[LN (EST SIZE)]^2		.019 (.013)	.021 (.013)		.028 (.012)	.028 (.012)
LN (FIRM SIZE)		−.228 (.113)	−.235 (.114)		−.054 (.103)	−.051 (.104)
[LN (FIRM SIZE)]^2		.020 (.007)	.020 (.007)		.006 (.007)	.006 (.007)
MILITARY SPEC		.190 (.044)	.191 (.044)		.201 (.042)	.200 (.042)
FABRICATION		.279 (.066)	.282 (.066)		.126 (.062)	.125 (.062)
NO FABRIC/ NO ASSM		−.144 (.128)	−.139 (.128)		.066 (.106)	.074 (.106)
FOREIGN OWN		.190 (.067)	.194 (.067)		.212 (.066)	.221 (.066)
AGE 16–30		−.000 (.049)	−.006 (.049)		−.063 (.047)	−.064 (.047)
AGE >30		−.135 (.055)	−.144 (.055)		−.096 (.052)	−.109 (.052)
HIGH SCHOOL+			.688 (.536)			1.583 (.507)
BA+			−.361 (.640)			.135 (.608)
RD_{1990}			−.183 (.150)			.161 (.113)
$BEALE_{12}$			−.082 (.056)			−.060 (.052)
$BEALE_{35}$			−.008 (.082)			−.002 (.078)
$BEALE_{69}$			−.002 (.085)			−.034 (.082)
CUTOFF POINT 1	1.163 (.067)	3.567 (.382)	3.768 (.504)	1.120 (.058)	2.024 (.339)	2.859 (.465)
CUTOFF POINT 2	1.326 (.068)	3.788 (.383)	3.989 (.504)	1.296 (.058)	2.232 (.339)	3.067 (.465)
CUTOFF POINT 3	1.613 (.069)	4.178 (.383)	4.380 (.504)	1.640 (.060)	2.634 (.339)	3.470 (.465)
Observations	6165	6165	6165	6171	6171	6171
Log Likelihood	−3961	−3215	−3210	−3994	−3554	−3547

Source: Authors' calculations, using 1993 Survey of Manufacturing Technology.

Appendix 6 (cont'd)
Technology Adoption Estimation Results: Ordered Probit Specification

	Technology Group 7			Technology Group 8		
Independent Variable	Coefficient (Std. Error)	Coefficient (Std. Error)	Coefficient (Std. Error)	Coefficient (Std. Error)	Coefficient (Std. Error)	Coefficient (Std. Error)
PROXIMITY	.390 (.109)	.339 (.114)	.080 (.130)	.500 (.111)	.428 (.116)	.247 (.123)
MULTI-EST		−.006 (.330)	−.089 (.332)		.714 (.318)	.658 (.320)
LN (EST SIZE)		.333 (.105)	.324 (.106)		.455 (.103)	.436 (.103)
[LN (EST SIZE)]^2		.005 (.011)	.006 (.011)		−.012 (.010)	−.010 (.010)
LN (FIRM SIZE)		−.014 (.089)	.003 (.089)		−.179 (.086)	−.165 (.087)
[LN (FIRM SIZE)]^2		.004 (.006)	.003 (.006)		.015 (.006)	.015 (.006)
MILITARY SPEC		.100 (.036)	.098 (.036)		.128 (.035)	.128 (.035)
FABRICATION		.085 (.053)	.086 (.053)		.072 (.052)	.075 (.052)
NO FABRIC/ NO ASSM		−.129 (.094)	−.121 (.094)		−.230 (.091)	−.222 (.091)
FOREIGN OWN		.133 (.058)	.147 (.058)		.122 (.057)	.138 (.057)
AGE 16–30		−.146 (.040)	−.143 (.040)		−.074 (.038)	−.074 (.039)
AGE >30		−.242 (.044)	−.261 (.044)		−.189 (.042)	−.207 (.043)
HIGH SCHOOL+			2.696 (.430)			2.366 (.427)
BA+			1.289 (.535)			−.265 (.490)
RD_{1990}			.255 (.092)			.127 (.094)
$BEALE_{12}$			−.017 (.044)			−.018 (.043)
$BEALE_{35}$			.043 (.065)			−.135 (.064)
$BEALE_{69}$			−.063 (.070)			−.038 (.067)
CUTOFF POINT 1	.673 (.055)	2.766 (.304)	4.392 (.404)	.665 (.064)	2.786 (.291)	3.873 (.389)
CUTOFF POINT 2	1.019 (.056)	3.165 (.305)	4.795 (.404)	1.047 (.065)	3.227 (.292)	4.317 (.389)
CUTOFF POINT 3	1.654 (.058)	3.881 (.305)	5.515 (.405)	1.610 (.066)	3.864 (.292)	4.956 (.390)
Observations	6121	6121	6121	6119	6119	6119
Log Likelihood	−5860	−5337	−5309	−6276	−5735	−5717

Source: Authors' calculations, using 1993 Survey of Manufacturing Technology.

Appendix 6 (cont'd)
Technology Adoption Estimation Results: Ordered Probit Specification

	Technology Group 9			Technology Group 10		
Independent Variable	Coefficient (Std. Error)	Coefficient (Std. Error)	Coefficient (Std. Error)	Coefficient (Std. Error)	Coefficient (Std. Error)	Coefficient (Std. Error)
PROXIMITY	.705 (.126)	.377 (.134)	.287 (.140)	.403 (.131)	.373 (.137)	.250 (.143)
MULTI-EST		.457 (.335)	.478 (.336)		.127 (.337)	.121 (.338)
LN (EST SIZE)		.355 (.111)	.332 (.112)		.402 (.107)	.396 (.107)
$[\text{LN (EST SIZE)}]^2$		.006 (.011)	.008 (.011)		−.006 (.011)	−.006 (.011)
LN (FIRM SIZE)		−.094 (.091)	−.102 (.091)		−.040 (.090)	−.040 (.091)
$[\text{LN (FIRM SIZE)}]^2$		.010 (.006)	.010 (.006)		.006 (.006)	.006 (.006)
MILITARY SPEC		.068 (.036)	.075 (.036)		.213 (.036)	.208 (.036)
FABRICATION		.413 (.057)	.412 (.057)		.206 (.056)	.208 (.056)
NO FABRIC/ NO ASSM		.449 (.089)	.460 (.089)		.108 (.093)	.116 (.093)
FOREIGN OWN		.075 (.060)	.080 (.060)		.186 (.059)	.188 (.059)
AGE 16–30		−.088 (.040)	−.088 (.040)		−.050 (.041)	−.052 (.041)
AGE >30		−.054 (.043)	−.055 (.043)		−.116 (.044)	−.124 (.045)
HIGH SCHOOL+			.314 (.430)			1.272 (.433)
BA+			−.973 (.504)			1.353 (.512)
RD_{1990}			.215 (.097)			.011 (.098)
$BEALE_{12}$			−.006 (.045)			−.011 (.045)
$BEALE_{35}$			−.030 (.066)			.065 (.067)
$BEALE_{69}$			.030 (.070)			.141 (.070)
CUTOFF POINT 1	.888 (.086)	2.568 (.309)	2.448 (.403)	.793 (.081)	2.858 (.306)	3.773 (.405)
CUTOFF POINT 2	1.044 (.086)	2.755 (.309)	2.636 (.403)	1.032 (.081)	3.133 (.306)	4.049 (.405)
CUTOFF POINT 3	1.437 (.087)	3.219 (.309)	3.100 (.404)	1.505 (.082)	3.667 (.307)	4.584 (.406)
Observations	6095	6095	6095	6115	6115	6115
Log Likelihood	−5969	−5328	−5322	−5621	−5143	−5135

Source: Authors' calculations, using 1993 Survey of Manufacturing Technology.

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DISCUSSION

John C. Haltiwanger*

The paper by Jane Sneddon Little and Robert K. Triest reflects careful empirical work with a rich and relatively new source of establishment-level data on the use of advanced manufacturing technologies. Using data from the 1988 and 1993 Surveys of Manufacturing Technology (SMT) combined with other establishment-level data from the Census and Annual Survey of Manufactures, Little and Triest explore important issues regarding the process of technological diffusion. Their basic question is: Do your technological neighbors matter? That is, are individual producers more likely to adopt advanced technology if other producers in their local geographic area have also adopted advanced technologies? The investigation into this question provides a fascinating glimpse into the complex process of adoption and diffusion of advanced technologies in the U.S. economy. Understanding this process is of fundamental importance for understanding the determinants of economywide and regional growth.

The results from the specific empirical exercises undertaken in this paper are a bit mixed. Using a broad measure of the number of advanced technologies an individual producer has adopted, they find that, even controlling for other factors, technological neighbors exhibit a positive and significant influence on adoption of advanced technologies. When the authors try to push the data a bit harder to investigate the connection between specific technologies and the detailed timing of adoption, the results are weaker. It is apparently more difficult to find a robust technological neighborhood effect in this more detailed level of analysis.

Since the analysis is carefully done, most of my comments reflect

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concerns about data and measurement issues as well as broader concerns about the interpretation of the results. To begin, I raise some data and measurement issues that should be considered in evaluating the current results.

Data and Measurement Issues

A key aspect of this study is the use of responses from the 1993 SMT that asked retrospectively about the timing of adoption of specific technologies. The survey asks respondents whether they have adopted a specific technology in the past two years, within the past two to five years, and more than five years ago. The timing is important in this context since the core empirical specification involves investigating the probability of adopting a technology between 1988 and 1993 as a function of initial conditions in 1988, where the latter includes information on the extent of technology adoption in the local geographic area.

Unfortunately, recent research with these data by Dunne and Troske (1995) indicates that the responses to the retrospective questions on the 1993 SMT are suspect, with substantial evidence of systematic recall bias. Respondents appear to systematically date adoption more recently than actually occurred. Consider, for example, the adoption of computer-aided design (CAD). Using the 1993 SMT, about 60 percent of respondents had this technology in use in 1993 and, based upon retrospective responses, only about 20 percent had this technology in use in 1988. This pattern suggests a tremendous increase in the use of CAD over this five-year period. However, the 1988 SMT indicated that about 40 percent of plants had this technology in use in 1988.

One possible explanation for this wide difference is that the 1988 and the 1993 SMTs represent different samples. Dunne and Troske investigate this by examining a matched sample of plants that responded to both the 1988 and the 1993 SMTs. Based upon a matched sample of approximately 2,300 plants, they examine the set of plants that had adopted CAD by 1988, based upon the 1988 SMT, and still were using CAD in 1993 based upon the 1993 SMT. One would hope that the responses to the retrospective questions in the 1993 SMT would be such that virtually all such plants would indicate that they had this technology in place in 1988. However, Dunne and Troske found that only 60 percent of such plants indicated in the retrospective responses that they had adopted CAD by 1988.

These measurement issues raise a variety of questions about the interpretation of the results in Little and Triest. Their strongest results are based upon the relationship between the number of technologies purportedly adopted between 1988 and 1993 and initial conditions. However, it may be that their dependent variable is a better measure of the number of technologies in place in 1993 rather than the number of technologies adopted between 1988 and 1993.[1] Thus, while their results indicate some degree of clustering of advanced technologies, the potential timing problems raise related questions about causality and in turn about the underlying source of this clustering. While many other geographic controls are considered in the analysis, omitted variable problems are always a concern. The potential problems from omitted variables are exacerbated if these results primarily reflect generic clustering as opposed to specific results on the timing of adoption. Further, the weaker results that emerge when the authors try to exploit the detailed data on specific technology adoption and timing may reflect these measurement problems.

Another measurement issue that may be important in this context is also raised by the work of Dunne and Troske (1995). Dunne and Troske find that "de-adoption" of specific technologies apparently is significant. That is, on the basis of the matched 1988–93 sample, a large fraction of establishments had a number of specific technologies in use in 1988 but no longer used them in 1993. For example, the de-adoption rate for LANs (local area networks) is 39 percent, while the de-adoption rate for pick and place robots is 37 percent. These large de-adoption rates suggest either additional measurement error problems or an interesting economic phenomenon. Under this latter interpretation, it looks as if many plants experiment with advanced technologies but may ultimately not use them. If this de-adoption phenomenon is real, then the process of adoption and diffusion should be modeled (theoretically and empirically) as one that involves gross positive and negative changes. In an environment with substantial gross positive and negative changes, an increase in the net adoption rate may reflect either an increase in the number of plants that have adopted the technology or a decrease in the number of plants abandoning the technology. The idea that a region or sector might be deemed more technologically advanced because the pace of de-adoption is slower there suggests that we should be thinking about the process of technical change in richer ways.

Interpretation of the Results

Beyond these measurement issues lie more basic questions about the interpretation and implications of the results. A key question in interpreting these results is whether the adoption of advanced technologies matters for outcomes that we really care about. Adoption of advanced technologies per se is not an objective of households, firms, or policymakers. They are concerned about the maximization of outcomes such as

[1] Indeed, the results of their Table 5 (rightmost columns) appear to confirm this hypothesis, since they obtain very similar results when using the number of technologies used as the dependent variable rather than the change in the number of technologies used.

the growth of income, employment, productivity, and profits (ultimately, of course, of economic welfare). One might presume that a tight link exists between indicators of the success of an individual company (and ultimately a particular region or the entire economy) and the adoption of the latest advanced technology. However, a number of recent studies of establishment-level behavior of employment and productivity growth raise a variety of questions about the link between observable establishment characteristics and measures of productivity and employment growth.[2]

While the literature on plant-level productivity and employment dynamics is still in its early stages, a number of patterns relevant for the current analysis are beginning to emerge. Even after controlling for differences in detailed industry, establishment size, establishment age, region, and factor intensities (such as energy or capital intensities), large residual differences across plants are found in the growth rates of employment and in productivity growth (either labor or total factor productivity). Indeed, within-group differences dwarf between-group differences, so that idiosyncratic factors dominate the determination of the fortunes of individual plants.

For those of us who have been involved in generating such results, considerable speculation has followed about what these idiosyncratic factors represent. Possible suggestions include differences in technology (broadly defined to include both "hardware" differences such as those investigated in this paper and differences in organizational capital), managerial ability, human resource practices, and just plain luck. The SMT data provide a means for evaluating the contribution of the adoption of specific advanced technologies to explain differences in outcomes across seemingly similar plants. Results in Doms, Dunne, and Troske (1995) suggest that differences in technology adoption rates are *not* particularly helpful in this regard. The latter paper finds that, after controlling for detailed industry, region, size, age, and capital intensity, there remains a positive and significant effect of adoption of advanced technologies on plant-level labor productivity.

However, even in this cross-sectional result, it is important to distinguish between statistical significance and overall economic significance. It turns out that differences in adoption rates account for only a very small fraction of the overall variation in labor productivity. All observable factors taken together account for about 28 percent of the cross-sectional variation in labor productivity, but the marginal contribution of the adoption rates is only about 1 percent. Even more striking are the results on labor productivity growth rates. For the same set of observables (in first differences now, as appropriate), Doms, Dunne, and

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[2] Relevant studies include Baily, Campbell, and Hulten (1992); Davis, Haltiwanger, and Schuh (1996); and Baily, Bartelsman, and Haltiwanger (1996).

Troske (1995) find that over a 15-year horizon, observables account for only about 10 percent of the variation across plants in labor productivity growth rates. Further, they find no statistically significant relationship between adoption of advanced technologies and labor productivity growth at the plant level. Putting these results together suggests that knowing whether individual plants have adopted an advanced technology is not particularly helpful in determining the variation in outcomes across plants.

Understanding the sources and dynamics of the differences across plants is important, not only for the micro dynamics of job and productivity growth but also for aggregate dynamics. It turns out that the high rates of job reallocation evidenced by the large differences in employment growth rates, and the large differences in productivity and productivity growth rates, are intimately linked. That is, the ongoing reallocation process of capital and labor tends to shake things up in the right direction. For example, Baily, Campbell, and Hulten (1992) and Baily, Bartelsman, and Haltiwanger (1996) show that an important component of aggregate productivity growth is the reallocation of resources away from less productive plants toward more productive plants (both between and within industries). In many ways, these are precisely the results one would expect from a market-oriented economy in which resources are allocated to their highest-valued uses. The striking nature of these findings from recent studies is the magnitude of the within-group variation and in turn its contribution to aggregate growth.

These results on the dominance of idiosyncratic factors and the importance of the reallocation processes in moving resources between seemingly similar plants do not imply that the processes of adoption and diffusion are unimportant for aggregate dynamics. Instead, these findings serve as a caution for both the micro and macro implications of the results on adoption and diffusion. The process of growth at the micro and ultimately the macro level involves a very noisy and complex process of change at the micro level. Apparently, considerable experimentation occurs on a variety of dimensions, including products, processes, locations, organizational structures, and human resource practices. Further, some plants that innovate and adopt new technologies do it well, while others do it poorly. Resources ultimately flow to the more successful, but the continuous underlying process of reallocation is both time- and resource-consuming, with some individuals undoubtedly hurt in the process. It is this large-scale, ongoing process of reallocation that lies at the heart of popular concerns about job insecurity and the link between technological change and job insecurity. Understanding the factors that generate this noisy process of growth and change and the factors that facilitate the necessary but sometimes painful ongoing process of reallocation should be a first-order priority.

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DISCUSSION

George N. Hatsopoulos*

I found the paper by Jane Sneddon Little and Robert Triest very interesting and also very gratifying: interesting because I believe that technology diffusion is at least as important as technology creation, and gratifying because it confirms some of my own empirical, subjective discoveries over my 40 years in high-technology manufacturing. I also appreciate the comments of Professor Haltiwanger because he, too, touches on things that I believe are important.

Over my years in general management, I have discovered that peer pressures, or peer effects, are more significant to the performance of the labor force than are influences by superiors. This is a very important lesson for businessmen to understand. It is really an expansion of the syndrome of "keeping up with the Joneses." If your peers do certain things, you are much more desirous of adopting tools or practices or even technologies than if you are told by your bosses, by the head of the corporation, to do certain things in a certain way. In fact, I have even found that subordinates can have, in many cases, just as much influence on local managers as their superiors. But certainly their peers have the most influence. Let me select as examples some of the findings of the paper that we are discussing right now.

Little and Triest have found that proximity has a strong effect on the adoption of technology, but they found that strength to be independent of establishment and firm characteristics. That is something that I would expect intuitively as a manager. I believe that technology adoption is influenced very much by interactions between employees of a certain level—middle management, foremen, from the plant and from neighbor-

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ing plants—and much less by the directives of some corporate headquarters, probably far away from the plant.

I would like to give you a specific example. A number of years ago we acquired a plant in the United Kingdom, up north in Manchester. That plant was making exactly the same products we were making in Auburn, Massachusetts. But we found its productivity was substantially lower, by a factor of two. In other words, the added value per hour of work was only half that of our Auburn plant. So, we started to study what was going on. Many factors were involved, including organization and technology adoption. I went up to Manchester and personally talked to the people running the plant and to their direct reports, the foremen, and I asked why they were not using certain technologies and organizational techniques. Basically, the conclusion I reached was that they were not doing it because their neighboring plants were doing something different. They were catering more to the neighboring plants. The product we were making is used by the paper industry, and Manchester has tremendous concentration of manufacturers for the paper industry. Their influence was so overwhelming that we had a hell of a time trying to change our plant's behavior. We did, eventually; we had to import some American managers and it was like pulling teeth, but we finally got them close. They are still less productive today than their American counterparts, but at least they are much closer.

Authors Little and Triest found another puzzle in the dependence of technology adoption on employment size. This finding might also be expected, for the usual reasons of economies of scale and access to capital. But they also found, and were puzzled to find, that the employment size of the plant per se matters, but the employment size of the firm to which the plant belongs is irrelevant. That, of course, can very well be explained, and it would be a conclusion I would reach, too. We have divisions all over the world, and we have plants all over the world. And I have found that it is very hard to change local culture. Access to capital is of course a central characteristic of the firm. Some firms have access to a lot of capital and have different capital costs than other firms, but I would not expect that factor to be anywhere near as dominant as the local culture. And, of course, plant size does affect technology adoption, because of the obvious economies of scale at the plant level.

Now, let me turn to the third puzzle, where Little and Triest found that the availability of employees with a high school diploma was a factor very strongly correlated with the adoption of technology, but they also found that technology adoption was negatively correlated with the presence of employees with college degrees. Now I do not quite believe the negative part of it, but I do believe in a zero effect. These effects are primarily due to the influence of middle management, usually foremen; and it is very important to these people to be in a location where a lot of employees with high school degrees are available.

In conclusion, let me say that I have found this discussion and this inquiry to be very important, not only to economists but also to managers. Plant culture can have much more influence, not only on productivity but also on innovation and on the economic growth of the plant, than any directives that come from a boss.