The Impact of Immigration on New Technology Adoption in U.S. Manufacturing

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March 14, 2005

[**] The views expressed here are those of the author and do not necessarily reflect the views of the Federal Reserve Bank of Philadelphia or the Federal Reserve System.

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Using detailed plant-level data from the 1988 and 1993 Surveys of Manufacturing Technology, this paper examines the impact of skill mix in U.S. local labor markets on the use and adoption of automation technologies in manufacturing. The level of automation differs widely across U.S. metropolitan areas. In both 1988 and 1993, in markets with a higher relative availability of less-skilled labor, comparable plants – even plants in the same narrow (4-digit SIC) industries – used systematically less automation. Moreover, between 1988 and 1993 plants in areas experiencing faster less-skilled relative labor supply growth adopted automation technology more slowly both overall and relative to expectations, and even de-adoption was not uncommon. This relationship is stronger when examining an arguably exogenous component of local less-skilled labor supply derived from historical regional settlement patterns of less-skilled immigrants.

These results have implications for two long-standing puzzles in economics. First, they potentially explain why research has repeatedly found that immigration has little impact on the wages of competing native-born workers at the local level. It might be that the technologies of local firms—rather than the wages that they offer—respond to changes in local skill mix associated with immigration. A modified two-sector model demonstrates this theoretical possibility. Second, the results raise doubts about the extent to which the spread of new technologies have raised demand for skills, one frequently forwarded hypothesis for the cause of rising wage inequality in the United States. Causality appears to at least partly run in the opposite direction, where skill supply drives the spread of skill-complementary technology.

Much has been written about how technology advance has raised the skill requirements in the U.S. labor market. Evidence of "skill-biased technological change," has been found in the association between the use of technology and the relative employment and wages of skilled workers when looking across workers (e.g., Krueger (1993)), plants (e.g. Dunne et. al. (2004)), and industries (e.g. Autor, Levy, and Murnane (2003)). It is also argued that the supply of skills has not kept pace with demand, leading to a growing gap between the earnings of skilled and unskilled workers (e.g. Katz and Murphy (1994)).

At the same time, however, the U.S. is in the midst of an immigration boom which has raised the proportion of workers who are less-skilled, particularly in certain parts of the U.S. Since 1970, immigrants – 40 percent of whom have less than a high school education (compared to 10 percent of native-born Americans) – have risen from 5 to 15 percent of the U.S. workforce. Furthermore, the impact of this boom has been geographically uneven: immigrants are highly concentrated in particular labor markets, and the proportion of the workforce which is less-skilled is higher in more immigrant-dense markets. Yet study after study has found that the local labor market impact of immigration on the relative employment rates and wages of less-skilled workers is almost zero.[1] High-immigration markets have succeeded in productively employing large amounts of unskilled workers despite the supposedly increased demand for skilled labor that the diffusion of new technologies has generated. How is this possible?

One way markets may be able to absorb less-skilled immigrants is by adopting less of the new high skill technologies.[2] The expectation that the local labor market impact of immigration

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[1] Borjas (1994) and Friedberg and Hunt (1995) provide reviews of this literature. Note that this is also despite evidence in other contexts that labor supply has an impact on wages (Hamermesh (1993)), including evidence that immigration has an impact at the national level (Borjas (2003)).

[2] Another explanation, discussed further below, is that local markets in the U.S. are each a small part of a large and integrated national economy so factor prices are insensitive to local factor mix. Lewis (2004b) found specialization in 3-digit industries to be unimportant, absorbing at most 10 percent of immigrant-induced skill mix differences

ought to be large derives from a standard view that production technology is invariant to input availability. Recent models of innovation (Acemoglu (1998)) and technology choice (Beaudry and Green (2000, 2003)) demonstrate that technology may respond to skill mix, which mitigates the usual "supply" effect. Below I present a modified version of Beaudry and Green (2000) which shows how a local market adapt to an influx of less-skilled workers by using less of a "modern" skill-intensive technology, allowing the new workers to be employed at existing wages. The idea that employers adapt technology to input availability is not new (see, e.g., Solow (1962), Johansen (1959), Habbakkuk (1962)) but it conflicts with the conventional view implied by recent studies that treat technology differences across plants or industries as exogenous in order to investigate the impact on wages or skill mix (Dunne et. al. (2004), Autor, Levy, and Murnane (2003)).

In this paper, an "adaptive" view of technology is evaluated using detailed plant-level data on the use of certain automation technologies introduced into manufacturing in the past few decades (see Table 1). Like with other recent technological advances, new plant automation techniques were projected to increase the relative employment of skilled workers, or as one study put it, "…jobs eliminated are semi-skilled or unskilled, while jobs created require significant technical background." (Hunt and Hunt (1983), p. xii.) Doms, Dunne, and Troske (1997) used the SMT data to show that more automated plants do indeed have a higher skilled employment share. They also showed, however, the same plants had a higher skill share well before they adopted the new technology. Given this, it is appropriate to ask the extent to which causality runs from skills to technology rather than the reverse. Manufacturing automation is particularly suited to evaluate the impact of immigration because less-skilled workers in SMT-covered

across markets. However, in light of recent indirect evidence that there may be quality specialization within narrow industries (Schott (2004)) this explanation remains a possibility.

industries, especially immigrants, are concentrated in labor-intensive assembly, welding, and other tasks that these technologies replace. (See Table 3.)

Technology data for this project come from the 1988 and 1993 Surveys of Manufacturing Technology (SMTs) and are supplemented with labor force data from Current Population Surveys and Censuses of Population. Using these data I find, in two separate cross-sections, that the higher the relative number of workers in a metropolitan area who were high school dropouts, the less automated the plants in the area were. In addition, between 1988 and 1993, plants' use of technology grew more slowly both overall and relative to forecasts where the relative number of dropouts in the local work force grew more quickly. Instrumental variables estimates, based on historical less-skilled immigration patterns, show that, if anything, simple least-squares correlations understate the impact of skill supply on the use of technology. A typical estimate is that a 10 percentage point (one standard deviation) increase in the less-skilled relative supply reduces the count of technologies in use at a typical worker's plant by roughly 0.5. Instrumental variables estimates reach near 2 technologies. A typical worker in the plants covered by the SMT was at a plant using 6 of these technologies, so the impact of skill supply is substantial.

These results provide a potential explanation for why the local labor market impact of immigration is small. To show this, below I present a modified two-sector model, in which, like in the original, an increase in the less-skilled relative supply affects the mix of technologies used but not relative wages.[3] The difference from the original model is that the different technologies are used to produce the <u>same</u> goods. An alternative interpretation – that the observed response of "technology" to immigration is in fact due a shift to in industrial mix toward less-skilled intensive industries that also use less technology – cannot be ruled out. Inconsistent with this alternative interpretation, however, controls for narrow (four-digit SIC) industry, and within

[3] Provided that the change is not so large as to move the economy outside its "cone of diversification."

those crude controls for product "quality," (Schott (2004)) have little impact on the strength of the relationship.

I. Theory

The idea that plants adjust technology to input availability is not new. This was a feature of "putty-clay" models (Solow (1962), Johansen (1959)) and was the core hypothesis of Habbakkuk's (1962) investigation of why the U.S. mechanized production ahead of the British in the nineteenth century. However, it seems to have fallen out of favor until it recently re-emerged in models attempting to explain why recent technological advance in the U.S. is "skill-biased." Models of directed technical change (Acemoglu (1998)) and endogenous technology choice (Beaudry and Green (2000,2003)) in essence argue that skill-complementary technologies have become more prevalent as a result of the rising skills of the U.S. workforce. Acemoglu models innovation. Beaudry and Green, in contrast, model the choice among available technologies. In their model, firms choose between two technologies of high ("modern") and low ("traditional") skill-intensity. A relative increase in skilled labor supply induces firms to adopt more modern technology.

A version of Beaudry and Green's model, modified to be appropriate for a local labor market, can be used to show how local labor markets in the U.S. might adapt to less-skilled immigration in a way that affects technology but not relative wages. The key change from their model is to make the supply of capital elastic. Beaudry and Green modeled the supply of capital as fixed, an assumption which is potentially appropriate for a large national economy but seems unrealistic for a local labor market.[4] As will be seen below, making the supply of capital elastic reduces the model to a modified two-sector model.

To illustrate a simple case of the model, suppose that perfectly competitive producers have available to them modern and traditional technologies which can each be represented by a Cobb-Douglass production function:[5]

$$Y_J = A_J L_J^{\alpha_J} H_J^{(1-\alpha_J)\beta_J} K_J^{(1-\alpha_J)(1-\beta_J)}$$

where J $\in$ {T,M} indexes the "traditional" (T) and "modern" (M) technologies; L_J represents less-skilled labor, H_J represents skilled labor, K_J represents capital used in technology J; and α_J, β_J, and A_J are parameters with $0<\alpha_J, \beta_J <1$ $\forall$J. Beaudry and Green's assumptions can be represented as restrictions on α_J and β_J. The only assumption critical for my purpose, however, is that the modern technology is relatively skill-intensive:

$$\frac{(1-\alpha_M)\beta_M}{\alpha_M} > \frac{(1-\alpha_T)\beta_T}{\alpha_T}$$

It is also important to emphasize that the outputs of the two technologies Y_T and Y_M are perfect substitutes – there is only a single good. The price of the good is normalized to 1.

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[4] Theoretical investigations of the local labor market impact of immigration typically assume the supply of capital is elastic.

[5] Although restrictive, a Cobb-Douglass technology implies an elasticity of substitution between skilled an unskilled labor (one) which is not that different than estimates (e.g. Hamermesh (1993)). This choice of technology also serves only the purpose of simple illustration. Beaudry and Green (2000) demonstrate their results hold for any constant returns to scale technology.

The next step is to solve for the minimum cost of producing a unit of output with each technology, given factor prices. Let w_L w_H, and r represent factor prices for less-skilled labor, skilled labor, and capital, respectively. The unit cost functions are:

$$(1)\quad C^J\left(w_L, w_H, r\right) = c_J w_L^{a_J} w_H^{(1-a_J)b_J} r^{(1-a_J)(1-b_J)} \text{ for } J\in \{T,M\}$$

where $c_J = A_J^{-1} a_J^{-a_J}\left[(1-a_J)b_J\right]^{-(1-a_J)b_J}\left[(1-a_J)(1-b_J)\right]^{-(1-a_J)(1-b_J)}$ for J∈ {T,M}. If both methods are in use (the economy is inside the "cone of diversification"), perfect competition implies $C^M(\cdot) = C^T(\cdot) = 1$, (zero profits – recall that the normalized output price is one). In keeping with the elastic capital supply assumption, r is assumed to be exogenous. Solving for w_L and w_H in terms of r:

$$(2)\quad w_L = c_T^{\frac{(1-a_M)b_M}{a_M(1-a_T)b_T - a_T(1-a_M)b_M}} c_M^{-\frac{(1-a_T)b_T}{a_M(1-a_T)b_T - a_T(1-a_M)b_M}} r^{\frac{(1-a_M)(1-a_T)[b_M(1-b_T)-b_T(1-b_M)]}{a_M(1-a_T)b_T - a_T(1-a_M)b_M}} \equiv w_L(r)$$

$$(3)\quad w_H = c_T^{\frac{a_M}{a_T(1-a_M)b_M - a_M(1-a_T)b_T}} c_M^{-\frac{a_T}{a_T(1-a_M)b_M - a_M(1-a_T)b_T}} r^{\frac{a_M(1-a_T)(1-b_T) - a_T(1-a_M)(1-b_M)}{a_T(1-a_M)b_M - a_M(1-a_T)b_T}} \equiv w_H(r)$$

(2) and (3) show that changes in the relative supply of skilled and unskilled labor have no effect on wages inside the cone of diversification: factor supplies do not appear in (2) and (3). This is the usual "factor price insensitivity" result of the two-sector model (Leamer (1995)).

The other purpose of this model is to show that an increase in the relative supply of less-skilled labor reduces the use of the modern method, i.e. the "Rybczynski theorem." This can be demonstrated by solving labor market clearing conditions. Let H and L represent the exogenously determined supplies of high- and less-skilled labor. By Shephard's Lemma the vector of factor demands equals the gradient of the cost function, so from (1):

$$
\begin{aligned}
L_J &= Y_J a_J c_J w_L^{a_J - 1} w_H^{(1-a_J)b_J} r^{(1-a_J)(1-b_J)} \\
&= Y_J a_J C^J(w_L, w_H, r)/w_L \\
&= Y_J a_J / w_L
\end{aligned}
$$

$$
\begin{aligned}
H_J &= Y_J (1-a_J) b_J c_J w_L^{a_J} w_H^{(1-a_J)b_J} r^{(1-a_J)(1-b_J)} \\
&= Y_J (1-a_J) b_J C^J(w_L, w_H, r)/w_H \\
&= Y_J (1-a_J) b_J / w_H
\end{aligned}
$$

for $J \in \{T,M\}$ (where the last step follows from zero profits). Substituting these into labor market clearing conditions, $H = H_T + H_M$ and $L = L_T + L_M$, produces, in matrix notation:

$$
\begin{bmatrix} a_T/w_L & a_M/w_L \\ (1-a_T)b_T/w_H & (1-a_M)b_M/w_H \end{bmatrix} \begin{bmatrix} Y_T \\ Y_M \end{bmatrix} = \begin{bmatrix} L \\ H \end{bmatrix}
$$

Let $D \equiv \begin{bmatrix} d_{LT} & d_{LM} \\ d_{HT} & d_{HM} \end{bmatrix}$ denote the matrix above, whose elements are all positive. Then,

$Y_M = |D|^{-1}(d_{LT}H - d_{HT}L)$ depends negatively on the relative supply of less-skilled labor so long as $|D|>0$. But this is equivalent to the condition $a_T(1-a_M)b_M > a_M(1-a_T)b_T$ which follows from the assumption that the modern technology is relatively skill-intensive. Thus use of the modern method falls with an increase in less-skilled relative labor supply, as we wanted. It also follows that use of modern machinery, K_M, falls as less-skilled relative supply increases, which is the implication tested below.[6]

This model has the nice feature that it is consistent with the stylized fact that immigration has little impact on relative wages in local labor markets, and has an additional testable implication that immigration should reduce use of skill-complementary capital. It has the drawback that by simply relabeling the modern and traditional "methods" as modern and traditional "goods" (in a small, open economy) one obtains the same implications; i.e., an apparent shift in the method of production might really be a shift in the mix of goods (say, from "low tech" metal fittings to "high tech" machine tools). However, one can distinguish the "methods" from the "goods" interpretation of the model by looking at how the technology used to produce the <u>same</u> goods varies with relative labor supply. For a given good, the "methods" interpretation says technology depends on relative labor supply, while the "goods" interpretation assumes technology is invariant to relative labor supply.

II. Data

Surveys of Manufacturing Technology

The technology data used in this project come from the 1988 and 1993 Surveys of Manufacturing Technology (SMT). Each polled a stratified random sample (described below) of around 10,000 manufacturing establishments with at least 20 employees in SIC industries 34-38

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[6] A final loose end is to show that the cone of diversification exists, i.e. that Y_M and Y_T can be both simultaneously greater than zero. The required condition is:

$$\frac{a_T}{(1-a_T)b_T} > \frac{w_L L}{w_H H} > \frac{a_M}{(1-a_M)b_M}$$

This outcome is feasible under the model's assumptions.

on the use of, plans for use of, reasons for use of (or for not using) 17 categories of advanced manufacturing technologies.[7] The industries covered by the SMT – fabricated metal products, industrial machinery and equipment, electronic and other equipment, transportation equipment, instruments and related products – make up a large part of the manufacturing sector (43 percent of value added and employment in 1987, according to U.S. Bureau of the Census (1989)).

The SMT technologies, described in Table 1, include processes used both in production and non-production activities, but most of the technologies are for use on the shop floor. Many also appear to replace raw labor, such as automated inspection (alternatively handled by semiskilled "production inspectors"), automated materials handling, and robots. This intuitive assessment of the role of these technologies fits with research showing a positive association between the use of these technologies and the skills of workers at the plant (Doms, Dunne and Troske (1997)). It is also borne out by research showing a negative association between computer use and use of labor in repetitive tasks (Autor, Levy, Murnane (2003)).

The SMT surveys also recorded other establishment characteristics, such as plant size, plant age, ownership, production type, military contractor status. These are listed in Table 2. The responses were in categories. Rather than drop observations that did not respond to one of these plant characteristics questions, I treated non-response as a separate category of "response" to each question.

The strata used to create each of the SMT samples consisted of 3-digit SIC industry by "class size" cells. There were three class sizes, defined by employment: 20 to 99, 100 to 499, more than 500 employees. (Plants with fewer than 20 employees were not in the survey). Within each strata, a simple random sample was taken, and a weight was recorded equal to one

[7] There was also a 1991 survey, not used in this analysis, which polled firms on the intensity of their use of these technologies in broad categories.

over the sampling rate for that strata. (The average sampling rate was about one-fourth.) Though the SMT was in theory a random sample, it was also a small sample. To insure that the present analysis would be geographically representative, I constructed new sample weights to properly reflect the geographic distribution of plants in the SMT-universe. I merged each plant in the SMT to the prior-year (1987 and 1992) Census of Manufactures. I then constructed new strata – 2-digit SIC industry by class size by metropolitan area. The equivalent to the original SMT weights would be to construct, in each of my new strata, a weight equal to the number of plants in the Census of Manufacturers universe divided by the number of plants in the SMT sample. However, this is not what I did. For the purpose of studying the impact on the labor force, I wanted weights that were representative of *employment*, not plants. So instead, I created a weight equal to strata employment in the Census of Manufactures divided by the number of plants in the SMT.[8]

III. Empirical Approach

The initial analysis will consist of cross-sectional regressions of technology use on the relative supply of less-skilled labor in the local work force, regressions of the form:

(4) $T_{jcn} = \alpha_j + \theta LS_c + \beta' X_{jcn} + \varepsilon_{jcn}$

where T_{jcn} represents the use of technology at plant *n* in industry *j* in city *c*; α_j represents a vector of industry dummies; and LS_c represents the relative supply of less-skilled labor in city-*c*. X_{jcn} is a vector of plant characteristics. The slope coefficient, θ, measures the impact of less-skilled

[8] Merging the SMTs to the prior-year Census of Manufactures had another purpose: it allowed me to merge in information about the plant not available in the SMT, such as employment (which is available only in categories in the SMT).

supply on the use of technology. If the theoretical model presented above is correct then θ will be negative in sign; under the null that technology is the same in all locations it is zero.

The most important set of control variables in this regression are the industry dummies, α_j. Industries vary in their use of technology and the skill mix: electrical machinery, for example uses both more technology and more skilled labor than the average SMT-covered industry. Also, open economy models predict differences in worker mix across markets are absorbed by differences in industry mix. An immigration-induced increase in the share of workers who were unskilled, for example, according to trade theory raises the share of the economy's output produced in unskilled-intensive sectors, which could show up as a lesser use of technology. Including industry dummies is equivalent to asking how much local skill ratios shift the method by which the <u>same</u> industries produce.

Plant size, measured by a continuous employment variable from the prior-year Census of Manufactures (1987 or 1992), will also be controlled for in some regressions. Dunne (1994) showed that the relationship between the use of technology and plant size was strong, while the relationship with another factor one might suspect was important, plant age, was weak. In the current context, it is nevertheless not entirely clear that a plant's size should be controlled for. After all, a plant's size may be endogenous, a channel through which local workforce skills affect the use of technology. Therefore, the regression without size controls is also of interest.

The Surveys of Manufacturing Technology also contain several other plant characteristics variables, described in Table 2, which will be controlled for in some regression specifications. One characteristic of interest is product price. Schott (2004) showed that even though there is little international specialization across four-digit industries, countries with a low relative supply of capital or skilled labor tend to specialize in lower quality products <u>within</u> four-digit industries.

Schott used unit values as a proxy for product quality in his analysis. To capture this possibility, I will include specifications that interact product price categories, indexed by *p*, with industry:

(4') $T_{jcpn} = \alpha_{jp} + \theta LS_c + \varepsilon_{jcpn}$

where α_{jp} represents a vector of industry x product price dummies. Though there are only six price categories in the data, they allow further, albeit crude, disaggregation of the data to test whether the use of technology differs across plants producing similar quality products.

Measuring Skill Mix

The primary measure of less-skilled relative labor supply used in this paper will be high school dropouts per high school "equivalent." The number of high school equivalents, defined here as the number of workers who are high school graduates plus one-half the number of workers with some college (1-3 years college) education, is a commonly used skill aggregate in research on skill biased technological change (for example, Autor, Levy, and Murnane (2003), Katz and Murphy (1992)).[9] Examining this skill margin – the very low educated relative to those with high school and vocational training – has two motivations. First, it is the margin on which foreign-immigration to U.S. labor markets has the strongest influence, and a major goal of this paper is to understand how immigrants are absorbed into U.S. labor markets. Second, it is a potentially appropriate skill margin to affect the use of the mostly production-related technologies covered by the SMT. Hunt and Hunt's (1983) survey of the potential impact of

[9] In this formulation, those with some college education are thought of as supplying labor inputs "equivalent to" half a high school educated worker and half a four-year college graduate worker. The qualitative results of this paper do not depend on the weight given to some college workers.

robotics, for example, talks about the loss of less-skilled jobs in favor of vocationally trained workers, and engineers. This margin also seems appropriate in light of the occupations of dropouts in SMT-covered industries, shown in Table 3 (computed using 1990 Census of Population microdata). It shows dropouts are highly concentrated in labor-intensive production occupations – assemblers, welders, and inspectors – which the automated technologies covered by the SMT might be reasonably argued to replace. Half of hours worked by dropouts in SMT industries are in just 10 less-skilled jobs. Immigrant dropouts are even more concentrated in these occupations. In contrast, only 43 percent of high school educated workers' hours and 26 percent of some college educated workers' hours (and 7 percent of college-graduate workers' hours) are in these same jobs – more educated workers have a greater presence in supervisory, managerial, and non-production tasks.[10] Also, in a given occupation high school and some college educated workers are more skilled – their average wages are higher – and they are likely better trained to install and use newer machines.

I will also examine the impact of other relative skill supply measures on the use of these technologies. In light of the association between the use of these technologies and college share at the plants in the SMT (Doms et. al. (1997)), as well as Hunt and Hunt's (1983) prediction that robotics would raise demand for engineers, one might be tempted to look also at the influence of college-educated relative supply. It is worth remembering, however, that college graduates have little presence in production occupations and instead tend to work in high-skill white-collar jobs in management, engineering, computer programming, and sales and marketing.[11] Nevertheless, the influence of college relative supply will also be examined.

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[10] Similar patterns also emerge in looking at a longer list of occupations – say, the top 20.

[11] The top ten occupations, by hours worked in 1990, of college graduates in SMT industries are: managers and administrators (18.9%), electrical engineers (9.0%), aerospace engineers (5.7%), sales representatives (4.8%),

Identification

Some argue that the use of new technologies, including the ones covered by the SMT, raise relative demand for skilled labor. Dunne and Schmitz (1995), for example, show plant-level average wages rise with the use of SMT-technologies. Doms et. al. (1997) find this, too, but, in contrast, find little evidence that changes over time in the use of SMT technologies were associated with faster growing employment share of skilled workers. Instead, Doms et. al. find that plants that adopted more technology had more skilled workers <u>prior</u> to adoption. Nevertheless, if it is true that technology raises skill demand, one might be concerned about interpreting θ from (4) as the causal impact of skill supply on technology use. Less-skilled workers might seek out "low-tech" markets where the relative demand for less-skilled labor is higher, generating a spurious correlation between technology use and local skill ratios.

To address this concern, I instrument for LS_c. The main instrument I use can be described as the share dropouts among "predicted" recent immigrants. The instrument takes advantage of the strong tendency of new immigrants from different parts of the world to settle into U.S. labor markets where immigrants from the same part of the world are already settled (as Bartel (1989) observed) and is based on historical country-of-origin mix of migrants in a given location.[12] Validity of this instrument is argued to come from the fact that it captures patterns of migration driven by family and cultural concerns rather than by labor demand.[13]

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mechanical engineers (4.4%), computer systems analysts (4.4%), accountants and auditors (4.1%), marketing, advertising and PR managers (3.8%), computer programmers (3.5%), and production supervisors (3.3%).

[12] Bartel grouped immigrants into 3 broad world regions: "Asians," "Hispanics," and "Europeans."

[13] Instruments of this nature are often referred to as capturing the "supply-push" part of immigration. George Johnson pointed out in discussion of a related paper that this supply-push term misstates where the variation is coming from – the instrument does not actually make use of conditions in the sending country to predict migrant flows; it is true, however, that the instrument assumes that the *national* volume of immigrant inflows is driven mainly by conditions in the sending countries, rather than the destinations.

The instrument assigns newly arriving immigrants to the cities where their countrymen were settled in 1970. 1970 is a near low point in U.S. history the presence of foreigners in the U.S. population, and largely precedes the modern wave of less-skilled immigration. Given the lag length, it is expected that immigration predicted on this basis is at most weakly related to local labor demand conditions. Indirect evidence in support of this assertion will be shown below. Similar to Card (2001), the instrument can be written as:

$$(5)\ \ DO_{ct}^{\perp} = \frac{\sum_g \frac{IMM_{gc,1970}}{IMM_{g,1970}} IMMDO_{gt}^{t-5}}{\sum_g \frac{IMM_{gc,1970}}{IMM_{g,1970}} IMM_{gt}^{t-5}}$$

IMM and *IMMDO* represent counts of immigrants and counts of immigrant dropouts, respectively, and *g* indexes region of origin, and t indexes year. IMM_{gt}^{t-5} represents the count of all immigrants from g who arrived in the U.S. in the past 5 years (between years *t* and *t-5*), while $IMMDO_{gt}^{t-5}$ represents the immigrants from *g* who arrived in the U.S. in the past five years and who are high school dropouts. Meanwhile, $\frac{IMM_{gc,1970}}{IMM_{g,1970}}$ represents the share of all immigrants from *g* living in city *c* in 1970. Therefore, $\frac{IMM_{gc,1970}}{IMM_{g,1970}} IMM_{gt}^{t-5}$ apportions recent immigrants from g to the cities where immigrants from that region were living in 1970; it is a prediction, based on historical settlement locations and recent national immigration, of recent immigration from g to city c. Summing across regions produces the denominator of (5), total 5-year immigration to c predicted on the basis of historical immigrant settlement patterns. The numerator of (5) does the same type of apportionment for recent immigrants who are dropouts, assigning them to the same locations as immigrants overall. Thus $DO_{ct}^{\perp}$ is the dropout share among recent "predicted" immigrants.

Table 4 lists the 16 world regions used to construct the instrument, in other words the "g" index in equation (5). It also shows the share of recent immigrants from each region in 1988 and 1993 – the years of the SMT surveys – and the share of recent immigrants who are dropouts in those years, computed using 1990 and 2000 public-use microdata.[14] The instrument apportions these recent immigrants from each part of the world according to the metropolitan area locations of immigrants from the same part of the world in 1970.[15] Mexicans, three-quarters of whom are dropouts, are by far the largest group of recent immigrants in both 1988 and 1993. The cities where Mexicans lived in 1970 (the top 5 were Los Angeles (32%), Chicago (7%), Houston (4%), El Paso (4%), and Anaheim (4%)) therefore have a large predicted dropout share. In contrast, eastern European or central Asian enclaves help predict a low dropout share.

The instrument does a remarkable job of predicting differences in the dropouts/high school equivalents across markets. Figure 1 and the first and fourth column of Table 5 show the relationship between the instrument and dropouts per high school equivalent in 1998 or 1993,

[14] For 1988, "recent" immigrants are in fact defined as those who report having arrived 1980-86. (This is the closest approximation to 5 years prior to 1988 that can obtained using the 1990 Census of Population). For 1993, recent immigrants are defined as those who arrived 1988-93, measured using the 2000 Census of Population. Only working age migrants with at least one year of potential work experience and in the labor force are included in the counts. The population weights in each Census were used to compute the counts.

[15] The locations of immigrants in 1970 are measured using the 1970 Census of Population. Metropolitan areas in the 1970 Census were constructed using county groups, with a county group included in a metropolitan area's definition if a majority of its population resided inside the 1990 boundaries of the metropolitan area. 1970 County population estimates were obtained from U.S. Dept. of Commerce, Bureau of the Census (1984). The 1990 boundaries of the metropolitan areas appear at http://www.census.gov/population/www/estimates/pastmetro.html. In contrast with the recent immigrant counts, the 1970 locations are computed using all immigrants age 16-75, regardless of labor force status.

measured using Current Population Survey merged outgoing rotation group files (MORGs).[16] F-stats exceed 60. This strong relationship reveals both the influence that immigration has on local skill supply and the strength of immigrant enclaves in attracting continued migration from the same part of the world, even 20 years later.

Mexicans alone do not drive the first-stage relationship. Columns (2) and (5) of Table 5 show that 1970 Mexican share enters significantly and separately into the first-stage regressions from the main instrument. Finally, supporting the validity of the instrument, controls for employment growth during the period in which the immigrant flows are measured (roughly the five years prior), added in columns (3) and (6), do not significantly affect the first stage.[17]

An advantage of this instrument is that similarly constructed instruments have been used in other research to demonstrate that local skill ratios have little impact on relative wages (Card (2001)) but nevertheless have a large impact on skill ratios in narrow industries (Lewis (2004b)). Using the same source of local labor mix variation to evaluate the impact on the use of technology allows these different results to be linked in a common model.

Other Empirical Issues

In most of the regressions below, the dependent variable will be simple count of the number of the 17 technologies in use by the plant.[18] Although summarizing how "high tech" a

[16] 1988 uses the average of the 1987-1989 MORGs, and 1993 uses the average of the 1992-1994 MORGs. Only those of working age (age 16-65 and old enough according to reported final years of schooling to be out of school) with at least one year of potential work experience who reported being in the labor force were included in the calculation. CPS final person weights were used in the computations.

[17] Employment is total private non-farm employment from the county business patterns county summary files. For the 1988 regression, employment growth is measured during 1980-86, the same years in which the immigrant flows are measured. (This has a correlation of 0.7 with 1983-88 employment growth.) Employment growth is measured 1988-93 for 1993. Controls for the wages and employment rates of high school dropouts and graduates are also insignificant and have little effect on the first stage.

[18] I assume, as the Census Bureau did throughout most of the reports they published on the results of the SMT (1989, 1994), that non-response to any technology use question indicates that the plant is not using that technology.

plant is in this way potentially masks some interesting variation, the count actually captures nearly 40 percent of the variation in the individual technologies and factor analysis suggests this as the principle component.[19] Doms et. al. (1997) summarized technology use in this way. Probably a bigger issue is that it would be desirable to know not just how much the local skill supply affects whether a technology is used, but also how much of it is used. This type of information is available for a limited number of the technologies in the 1993 survey.

In order to obtain the correct standard errors, the regressions were run in two steps: first, the number of technologies was regressed on plant characteristics and city dummies; second, the estimated city dummies were regressed on the city's dropout share. Regressions were weighted to be representative of employment; correctly interpreted, therefore, they measure the impact of citywide dropout share on the number of technologies at "the average employee's plant," but nevertheless they will frequently be described below as the impact at "the average plant."[20]

The regressions were run across 143 cities for which all the necessary data were available.[21] In 1988, the average employee in the SMT-universe in these cities was at a plant using 6 of these technologies; by 1993 this had risen only slightly, to 6.2 technologies. Some of the technologies actually declined in use between 1988 and 1993; in fact, the growth in use is confined to computer-based technologies listed in categories I and V of Table 1.[22] In both 1988 and 1993 there is also wide variation across plants in the use of technology. More than ten

[19] Beede and Yang (1998) illustrate the potential pitfall of this summary measure: they find that the effect on productivity, employment, and earnings vary by technology, and sometimes even differing in sign. I also find some heterogeneity, but, in contrast, I cannot reject that the impact of the local dropout share on the use of these technologies is uniformly negative. Given this, the effect of dropout share on the number of technologies concisely sums up the effect of dropout share on each technology.

[20] The employment weights are described in the data section.

[21] The biggest loss of metropolitan areas comes from the requirement that each area must be observable in the 1970 Census of Population, which is used to construct the instrument. Another restriction is that there be at least one plant in the both the 1993 and 1988 SMT surveys.

[22] McGuckin et. al. (1998) also found the 1988-93 increase in use was confined to these categories of technology.

percent of the variation across plants can be accounted for by variation across the 143 labor markets used in the regressions, even when holding constant industry mix across those markets.[23]

Finally, before turning to the results, how well does metro area-wide dropout share actually reflect the supply of labor available to manufacturing plants in SMT industries? To find out, Figure 1 plots dropouts per high school equivalent in SMT industries (SIC 34-38) against the dropouts per high school equivalent in the city's labor force overall (for my sample of cities). The relationship does not seem to be far from the 45 degree line in either 1988 or 1993. More generally, Lewis (2004b) finds a strong and systematic relationship between citywide dropout share and dropout share in narrow industries. Figure 1 also demonstrates the tremendous variation across labor markets in the relative supply of less-skilled labor.

IV. Cross-Sectional Results

Table 6a presents estimates of (4). Columns (1) and (3) show OLS estimates for 1988 and 1993, respectively. The first row shows OLS estimates with no additional controls. The coefficient -4.67 for 1988 says that when the relative supply of dropouts rises by 10 percentage points – slightly less than one standard deviation – the average plant in the city uses 0.467 fewer technologies. A similar estimate is obtained in 1993 data. This relationship may partly reflect differences in industry mix across locations: areas with more unskilled labor may have more low-technology types of industries. The second row therefore controls for detailed industry, dividing SMT plants into 161 four-digit industries. Interestingly, this does not weaken the relationship! Even within narrow industries, therefore, the use of these technologies varies strongly with the local skill share. To further control for product quality within industry, the

[23] This figure is the amount by which the R^2 increases in going from a plant-level technology regression without city dummies to one with city dummies.

third row interacts four-digit industry with the product-price categories (inspired by Schott (2004)). The influence of local skill supply is robust to controls for this proxy for product in both 1988 and 1993.

One might argue that what is really going on is that the use of technology influences the skill composition of the local workforce: low-skill workers are attracted to markets where, for some reason, the use of these (potentially) labor-replacing technologies is lower. To find out if this is the case, we now turn to instrumental variables estimates, using the instrument $DO_{ct}^{\perp}$ described in equation (5). Two-stage least squares estimates are presented in columns (2) and (4). Note that these estimates are *larger* than the OLS estimates. In other words, if anything dropouts differentially live in markets with higher technology use, biasing OLS estimates toward zero.[24]

The last three rows of Table 6a present specifications with other plant-level controls. The fourth row shows a specification which controls also for plant employment, entered as a sixth-order polynomial.[25] Dunne (1994) showed plant size has a strong influence on the use of these technologies, though in this context, where plant size may be endogenous, it is not necessarily appropriate to use it as a control variable. Nevertheless, one finds that the influence of local dropout shares on technology use remains significant, even conditional on plant size. The next row adds in other plant-level controls, listed in Table 2, entered as dummy variables for each category of response. Even with these controls added, the dropout share has a statistically significant sizeable negative effect on the use of technology in all four columns. Finally, the 1993 SMT asked questions about foreign ownership and how much of a plant's production was exported to foreign countries; prior research has found both of these variables to be associated

[24] In addition, any attenuation of the OLS estimates due to measurement error is eliminated in the IV regressions.
[25] Terms beyond sixth order were never found to be significant.

with higher plant productivity (Bernard et. al. (2002)).[26] The last row of the table includes these variables as controls; they have little impact on the estimates.

A more continuous measure of technology use is also available in the 1993 survey. For a limited number of technologies, the 1993 survey asked plants to report the "number of dedicated workstations (or items of equipment)." The technologies covered by this question include computer aided design, engineering, and manufacturing; numerically controlled machines; materials working lasers; pick and place and other robots; programmable controllers; and computers used for control on the factory floor.[27] These make up more than half of the technologies in use at the average worker's plant in 1993. Using this, I created a measure of technological intensiveness, "high tech machines per employee," equal to, for each plant, the number of machines (summed across these technology categories) divided by plant employment. Almost all of the variation comes from differences in the use of programmable controllers, however. The average worker's plant in 1993 used 0.11 of these machines per employee, or roughly one machine per nine employees. Many plants used zero machines per employee.

Table 6b shows estimates of (4) with this dependent variable for the same specifications as were used in Table 6a. All of the estimates are negative and sizeable, though they are imprecisely estimated. Thus the dropout share affects not only the "extensive" margin – whether technology is used – but the "intensive" margin, how much technology is used.

Note that in both Tables 6a and 6b, the saturated IV estimates are not statistically distinguished from the simple OLS estimates with no controls. The results point consistently to

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[26] The foreign ownership question was "Does a foreign entity (company, individual, government, etc.) own, directly or indirectly, 10 percent or more of the voting stock or other equity rights in this plant?" with possible answers "yes" "no" and "don't know." The export question was "What percent of this plant's total value of shipments are exported for direct sale? *Include shipments to foreign subsidiaries*" with possible answers "None" "Less than 10 percent" "10-19 Percent" "20-49 Percent" "50 percent or more."

[27] Or, in other words, technologies #1,2,5,6,7,8,16, and 17 in Table 1.

the interpretation that the relative availability of less-skilled labor in a local market depresses the use of automated manufacturing technology by otherwise similar plants.

Robustness

These results are robust to other formulations of relative less-skilled labor supply. Appendix table A1 shows the results for using dropouts per labor force, rather than per high school equivalent, as the independent variable. Once one adjusts for the fact that the standard deviation of this variable is between half and three times as large as the independent variable used earlier, estimates are all of a similar order of magnitude.

These results by definition imply that the relative supply of workers with at least a high school education raises use of these technologies. In light of evidence that use of these technologies is higher at plants with relatively more college-educated workers (Doms et. al. (1997)), one might also wish to examine more finely the impact of relative supply of these higher levels of education. Therefore, I have also run regressions of the number of technologies on share with at least high school education, broken up into the just high school (HS_c), some college but no four-year degree (SC_c), and four-year college graduate shares (GR_c):

$$T_{jcn} = a_j + q_2 HS_c + q_3 SC_c + q_4 GR_c + b'X_{jcn} + e_{jcn}$$

To get at the immigrant impact, I constructed three instruments similar to (5) but dividing recent inflows of immigrants in these three education groups:

$$HS_{ct}^{\perp} = \frac{\sum_g \frac{IMM_{gc,1970}}{IMM_{g,1970}} IMMHS_{gt}^{t-5}}{\hat{M}_{gt}^{t-5}}, SC_{ct}^{\perp} = \frac{\sum_g \frac{IMM_{gc,1970}}{IMM_{g,1970}} IMMSC_{gt}^{t-5}}{\hat{M}_{gt}^{t-5}},$$

$$GR_{ct}^{\perp} = \frac{\sum_g \frac{IMM_{gc,1970}}{IMM_{g,1970}} IMMGR_{gt}^{t-5}}{\hat{M}_{gt}^{t-5}}$$

where $\hat{M}_{gt}^{t-5} \equiv \sum_g \frac{IMM_{gc,1970}}{IMM_{g,1970}} IMM_{gt}^{t-5}$ and $IMMHS_{gt}^{t-5}$, $IMMSC_{gt}^{t-5}$, $IMMGR_{gt}^{t-5}$ represent the volume of recent immigrant arrivals of high school, some college, and 4-year college graduate levels of education respectively. These results of these regressions support the specification I have performed in this paper: the relative supply of these groups tends to raise use of technologies, but the effect is concentrated in the high-school educated and some-college range. The supply of some college educated workers has a larger positive effect than does the supply of high school only workers; the supply of four-year college graduates has little impact on the use of these technologies. The latter is consistent with the fact that college graduates have little presence production activities.

V. Do Changes in Skill Mix Affect Changes in Technology Use?

Another, perhaps stronger, test of whether local skill mix affects the use of technology is to ask whether when as a market's mix of workers changes, the plants in that market adjust their use of technology. This question could be answered by first differencing the data used to run the regressions in Table 6a. However, a nice feature of the SMTs is that some plants were sampled in both years which allows first difference regressions to be run at the plant level using a balanced panel – i.e. examining how the same plants change their use of technology when the local skill supply changes. An advantage of this approach is that it implicitly removes any unobserved (fixed) attributes of a plant which affect its use of technology. By itself, however, this approach could still be biased by plant attributes whose influence is changing over time (say, if there were differential trends in technology adoption across industries). Therefore, it still may be important to control for baseline plant characteristics. A disadvantage is that requiring that plants appear in both datasets reduces the sample size considerably, and may produce a sample which overrepresents large plants (McGuckin et. al. (1998)).

The panel approach also allows controls for baseline technology use. This control has several interpretations. First, it captures the "dynamics" of technological change: adoption of new technologies often follows an "S-shaped" pattern over time (e.g. Griliches (1957)) which can be captured by regressing changes on initial levels. Baseline technology use has another useful interpretation in this case: it can roughly be construed as a lagged *change* in the use of technology, since adoption of most SMT-technologies occurred not long before 1988. For example, according to a large, nationally representative survey of plants in SMT-industries, in 1983 only six percent of manufacturing plants used any type of automated assembly, only 3 percent of plants used any type of robotic machine tools, though at least one-quarter of plants were already using numerically-controlled machines (*American Machinist* (1983)). Regressions which control for technology use in 1988 therefore roughly ask if local influxes of dropouts affect plants' trend-adjusted technology adoption.

Another available control is plants' initial plans for adding technology in the next five years, asked in the 1988 survey. As it turns out, plants' plans for adding technology considerably overstated how much they ended up adding, but the variable still correlates strongly with realized changes in the use of technology. Controlling for this allows us to find out if increases in the availability of unskilled labor cause firms to deviate from their initial plans for technological upgrading.

Results

OLS and 2SLS regression results for a panel of 1,474 establishments which could be observed in both the 1988 and 1993 surveys are shown in Table 7. In order to correct for the fact that the dropout share varies only across cities, errors are clustered at the city level. Regressions are weighted using the employment weights (for the base year), as before.[28] The 2SLS estimates use the instrument $DO^{\perp}_{c,1993}$ which was used for the 1993 cross-section above.[29]

The first row shows OLS and 2SLS estimates with no controls. Both the OLS and 2SLS estimates are negative and similar to the cross-sectional estimates. Unfortunately, the standard errors are also quite large, a problem of working with such a small sample. The second row adds in dummies for a plants' 1988 four-digit SIC industry, which reduces the OLS but not the 2SLS estimate. Even with these controls, one might still be concerned that the observed effect derives partly from the impact that changes in dropout share have on changes in industry mix (as simple open economy models predict). As a safeguard against this possibility, estimates in the third row (and below) also include controls for four-digit industry in 1993; estimates are not lowered by their inclusion.[30]

The fourth row adds controls for the number of technologies in use in 1988 which, to be as general as possible, is specified as 17 dummy variables corresponding to the number of

[28] Results are robust to using the average of the 1988 and 1993 weights.
[29] In each of the specifications presented, the first stage regression coefficient is about 0.09, with an F-stat around 20, except the regression with no controls, which has an F-stat of 516.
[30] Another way to hold constant industry mix is to restrict the sample to plants which do not change industries between 1988 and 1993. Estimates for this subsample are larger in magnitude.

technologies in use (though a simple linear control performs similarly).[31] The plants with more technology in 1988 saw slower growth in technology use 1988-93: there was convergence across plants in technology use. This control soaks up one-quarter of the variation in the dependent variable and reduces the standard errors considerably. It also raises the point estimate, indicating that the less-skilled labor supply grew faster in places that, based on initial levels of technology use, one would have expected to have fast technology growth – places that had low technology use initially. Once this is controlled for, the estimates are larger. Instrumental variables estimates now reach near two technologies per standard deviation increase in the independent variable.

The third row adds a control for the number of technologies plants reported in 1988 that they planned to add in the next five years. A regression of the actual change in the number of technologies on this produces a strongly significant coefficient around 0.25. This is far below one, indicating that plants were overly optimistic about how much technology that they would add between 1988 and 1993.[32] Still, the variable has a strong positive relationship with the net change in the amount of technology in use, and adding it as a control does not reduce the coefficient on the change in dropout share. It appears, therefore, that influxes of less-skilled workers caused firms to scale back their initial plans for adding technology.

The subsequent rows of Table 7 add in other baseline controls. The next row adds a sixth-order polynomial in plant size in 1988, which has little impact. The last row adds in the other controls from Table 6a, which reduces the estimates slightly. The OLS estimate in this

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[31] If one runs the linear version, the coefficient on the lagged number of technologies is around -0.5.

[32] This coefficient alone is not an accurate test of how well firms forecast future technology-use plans. A better test would be to look at the individual technologies plants said they planned to add. In addition, the dependent variable in the regression is a net change in the number of technologies in use, while the control is only for technologies that firms planned to add: firms were not asked about whether they planned to reduce the use of technology.

specification is not statistically distinguished from zero, though the 2SLS estimate remains large and significant.

Another implication of these estimates is worth noting. During this period, technology use at the average plant grew by a scant 0.2 technologies. The magnitude of these estimates therefore implies many plants de-adopted technology as a result of less-skilled immigration to the local market. (In fact, McGuckin et. al. (1998) found de-adoption to be not uncommon in these data.) This behavior supports the view that technology choice is influenced by cost pressures, rather than being on an inevitably upward path.

Specification Test

Finally, as a specification check we regress plant's plans to add technology in the next five years on the future change in dropout share, a test of whether the negative relationship between technology use and dropout share found so far is driven by the endogenous migration of less-skilled workers to markets with low levels of technology. Table 8 shows the same specifications as Table 6a, except that the dependent variable is now the number of technologies plants reported in 1988 they would add by 1993, and the independent is the change in dropout share between 1988 and 1993. OLS estimates are in column (1). All of them are positive, though not statistically significant. 2SLS estimates, which use as the instrument $DO^{\perp}_{c,93}$, are shown in column (2). These are also positive, of similar magnitude, and statistically insignificant. This is a reassuring finding, supporting the idea that the direction of causality does indeed run from skill supply to technology use and not the other way around. If anything, in fact, dropouts tend to differentially migrate to future "high-tech" markets. It is not clear why this would be the case, but it is consistent with a bias towards zero in the OLS estimates suggested by the fact that the 2SLS estimates are generally larger than OLS estimates.

V. Discussion

In all of the analysis presented in this paper, a higher local relative supply of less-skilled labor, especially when induced by immigration, depresses the use of manufacturing automation technologies. This suggests that plants use automation as a substitute for less-skilled labor, as one might suspect on a priori grounds. This is similar to what Lewis (2004b) found for on-the-job use of computers and what Nestoriak (2004) found for computer investment. Lewis found computer use rose less rapidly as the growth in the local relative supply of less-skilled labor increased due to immigration. Nestoriak (2004) found computer investment was higher in counties with a relative employment of skilled labor. Researchers have also argued for some time that computer-based technologies lower relative demand for less-skilled labor (Krueger (1993)). This paper finds the reverse – the relative supply of less-skilled labor reduces demand for technology. It is possible for both to be to some extent true, but the findings of this paper should cast doubt on the extent to which technological advances have raised the relative employment of skilled workers.

The results also potentially explain the why the local labor market impact of immigration on native-born wages has consistently found to be so small (Borjas (1994), Friedberg and Hunt (1995)). It may be that the technology employers use – rather than the relative wages they pay – adjusts to local labor mix. The results of this paper are consistent with a Beaudry and Green (2000)-style model of endogenous technology choice, in which areas with a high relative supply of less-skilled labor make greater use of less-skilled intensive production methods. In such a model, less-skilled relative wages are insensitive to relative supply. This model is therefore a strong candidate for explain how local labor markets adapt to immigration.

The main caveat on these results is that what I interpret as differences in "technology use" may also reflect systematic differences in product mix below the level of industry detail observable to me (four-digit SIC). Schott (2004) provides indirect cross-country evidence that product quality within narrow industries varies according the local skill and capital supply. To address this, I controlled for a crude measure of product quality within industry, and found that this had little effect on the results. While this does not rule out that more detailed data would reveal that the results were driven by differences in product quality, it is encouraging for the interpretation I give to the data.

VI. Conclusion

This paper has explored the impact of local skill supply on the use of automated technologies by manufacturing plants. In standard theories of technological adoption, local skill supply should have no impact on the use of technology. In contrast, I find that the use of these technologies in both 1988 and 1993 was strongly decreasing in the local relative supply of less-skilled (high-school dropout) labor. The result is robust to controls for detailed (four-digit SIC) industry and other plant characteristics, and if anything, the effect is larger when using arguably exogenous historical patterns of less-skilled immigration as an instrument. Furthermore, when there share of workers who are dropouts in a plant's local labor market rises, the plant reduces growth in the use of automated technology both overall and relative to its initial plans and sometimes even de-adopts technology.

The results of this paper are consistent with a model which can explain why repeated studies have turned up little evidence that immigrant shocks to local skill ratios have an impact on relative wages. Recent theoretical models of endogenous technological choice (Beaudry and Green (2000)) remind us of the theoretical possibility that employers may adapt to less-skilled immigration by altering the method of production, leaving relative wages insensitive to supply (like in a standard "two sector" model). The facts so far fit this model – production methods (in narrow industries) are sensitive to local skill mix, while relative wages are not.

Finally, the results of this paper are consistent with recent cross-country evidence that computer adoption responds to skill mix (Caselli and Coleman (2003)), a fact which may help explain the persistence of income differences across countries (Keller (2004)). The finding that even within the U.S. there are major differences in the use of technology related to local skill shares provides strong support for this view.

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<u>Table 1</u>. Description of Technologies Covered in Surveys of Manufacturing Technology

I. Design and Engineering

1. *Computer-Aided Design (CAD) and/or Computer-Aided Engineering* – "Use of computers for drawing and designing parts or products and for analysis and testing of designed parts or products."
2. *Computer-Aided Design (CAD)/Computer-Aided Manufacturing (CAM)* – "Use of CAD output for controlling machines used to manufacture the part or product."
3. *Digital Data Representation* – "Use of digital representation of CAD output for controlling machines used in procurement activities."

II. Fabrication and Machining

4. *Flexible Manufacturing Cell (FMC)/Flexible Manufacturing System (FMS).* <u>FMC</u> – "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."
   <u>FMS</u> – "Two or more machines with automated material handling capabilities controlled by computers or programmable controllers, capable of multiple path acceptance of raw material and multiple path delivery of finished product. A FMS may also be comprised of two or more FMC linked in series or parallel."

5. *NC/CNC Machine* – "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 while CNC machines are controlled electronically through a computer reading in the machine."
6. *Materials Working Laser* – "Laser technology used for welding, cutting, treating, scribing and marking."
7. *Pick and Place Robots* – "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."
8. *Other Robots* – "A reprogrammable, multifunctional manipulator designed to move materials, parts, tools or specialized devices through variable programmed motions for the performance of a variety of tasks."

III. Materials Handling

9. *Automated Storage and Retrieval Systems (AR/RS)* – "Computer controlled equipment providing for the automatic handling and storage of materials, parts, subassemblies, or finished products."
10. *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."

(Continued)

Table 1. (Continued)

IV. Inspection and Quality Control

Automated Sensor Based Inspection And/Or Testing Equipment – "Includes automated sensor based inspection and/or testing performed on incoming or in-process materials, or performed on the final product."

11. *Performed on Incoming Materials*
12. *Performed on Final Product*

V. Communications and Control

13. *Technical Data Network* – "Use of local area network (LAN) technology to exchange technical data with design and engineering documents."
14. *Factory Network* – "Use of local area network (LAN) technology to link information between different points on the factory floor."
15. *Intercompany Computer Network* – "Use of network technology to link subcontractors, suppliers and/or customers with the plant."
16. *Programmable Controllers* – "A solid state industrial control devise that has programmable memory for storage of instructions, which performs functions equivalent to a relay panel or wired solid state logic control system."
17. *Computers Used for Control on the Factory Floor* – "Exclude computers imbedded within machines, or computers used solely for data acquisitions or monitoring. Include computers that may be dedicated to control but are capable of being programmed for other functions."

Source: US Bureau of the Census (1989), US Bureau of the Census (1994).

Table 2. Plant Characteristics Variables in the Surveys of Manufacturing Technology

1. Plant Age. "How Many Years Has this Establishment Manufactured Products at this Location?" (A) Less than 5 years; (B) 5-15 Years; (C) 16-30 Years; (D) Over 30 Years.
2. Nature of Manufacturing. (A) Fabrication/Machining; (B) Assembly; (C) Fabrication/Machining and Assembly; (D) Neither Fabrication/Machining nor Assembly.
3. Product Price. "What is the average market price for MOST products of this plant?" (A) Less than $5; (B) $5-$100; (C) $101-$1,000; (D) $1,001-$2000; (E) $2,001 to $10,000; (F) Over $10,000.
4. Market. "What is the market for MOST of the products of this plant?" (A) Consumer (personal use by household); (B) Commercial (e.g., offices, hospitals, services, etc.) (C) Industrial (manufacturing, mining, construction, and utilities); (D) Transportation; (E) Government; (F) Other *in 1993 and* (F) Can't Specify *in 1988*.
5. Any Military. "Are any of the products produced in this plant manufactured to military specifications?" (A) Yes; (B) No; (C) Don't know.
6. Percent Shipped to Federal Defense Agencies. (A) 1-25%; (B) 26-75%; (C) Over 75%; (D) None; (E) Don't Know.
7. Percent Shipped to Prime Contractors of Federal Defense Agencies. (A) 1-25%; (B) 26-75%; (C) Over 75%; (D) None; (E) Don't Know.

Source: US Bureau of the Census (1989), US Bureau of the Census (1994).

Table 3. Top Occupations of High School Dropouts by Share of Hours Worked

SMT industries, 1990

	Dropouts	
	All	Immigrant
Assemblers	13.8%	15.0%
Electrical Equip. Assemblers	5.5%	9.3%
Welders and Cutters	5.3%	4.6%
Machine Operators, Not Spec.	5.1%	7.4%
Supervisors, Production Occs	5.0%	4.3%
Machinists	5.0%	5.1%
Miscellaneous Machine Ops	3.4%	5.3%
Production Inspectors	3.1%	2.9%
Laborers	2.6%	2.7%
Janitors and Cleaners	2.1%	1.8%
Top 10 Occupations	**50.9%**	**58.5%**

Data Source: 1990 Census of Population public-use microdata. Among those working in industries covered by the SMT, figures show share of hours worked by members of a group (e.g. high school dropouts) employed in the given occupation.

Table 4. Origin Mix and Skills of Recent Immigrants in 1988 and 1993

Origin Region	Shr. of Recent Imms		Rec. Imm Shr. Dropout	
	1988	1993	1988	1993
	(1)	(2)	(3)	(4)
Mexico	0.257	0.298	0.756	0.670
Caribbean	0.082	0.077	0.423	0.334
Central America	0.101	0.086	0.602	0.591
China, HK, Singapore	0.060	0.062	0.239	0.188
South America	0.072	0.063	0.283	0.226
SE Asia/Pac. Island	0.075	0.066	0.373	0.351
Korea & Japan	0.044	0.031	0.140	0.086
Philippines	0.063	0.052	0.114	0.094
Canada, Aust/NZ/UK etc.	0.038	0.037	0.103	0.064
India, Pakistan, Centr Asia	0.048	0.055	0.126	0.103
Russia & Eastern Europe	0.034	0.075	0.177	0.100
Southwestern Europe	0.016	0.011	0.439	0.256
Northern Europe & Israel	0.021	0.024	0.086	0.086
Turkey, N. Africa, Mid. East	0.032	0.025	0.119	0.129
Other Africa	0.026	0.029	0.097	0.120
Cuba	0.030	0.011	0.535	0.381

Data Source: 1990 and 2000 public-use Census of Population. Columns (1) and (3) shows statistics on the 3,118,709 immigrants who reported arriving in the U.S. between 1980-86 according to the 1990 Census while column (2) and (4) shows the same statistics on the 3,631,347 immigrants who reported arriving between 1988 and 1993 according to the 2000 Census. Only working-age immigrants (age 16-65 and old enough to have completed reported years of school) not living in group quarters, with at least one year of work experience, and who report being in the labor force are included in the calculations for columns (1)-(4).

Table 5. First Stage Regressions, 1988 and 1993

Variable	1988 (1)	1988 (2)	1988 (3)	1993 (4)	1993 (5)	1993 (6)
"Predicted" Dropout Share	0.50	0.23	0.22	0.66	0.40	0.41
	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)
1970 Share of Mexican Imms		0.76	0.77		0.84	0.84
		(0.08)	(0.09)		(0.10)	(0.11)
"5-year" prior employment growth*			0.02			-0.01
			(0.05)			(0.09)
R^2	0.31	0.56	0.56	0.42	0.62	0.62
F-Stat, Instruments	62.1	89.3	88.7	103.0	112.8	108.6

*Measured 1980-86 for 1988 regression (the years in which immigrant inflows were measured). See text for details of data sources and sample. Regressions weighted by employment in SMT industries, measured using 1988 or 1993 County Business Patterns county summary files.

Table 6a. The Impact of Citywide Dropout/High School Equiv on # of Technologies in Use

Controls	1988 N=6,571 OLS (1)	1988 N=6,571 IV (2)	1993 N=4,757 OLS (3)	1993 N=4,757 IV (4)
No Controls	-4.67	-3.92	-3.83	-2.69
	(1.29)	(2.25)	(1.01)	(1.52)
4-digit-industry	-4.17	-7.67	-4.36	-5.06
	(1.17)	(2.10)	(0.90)	(1.36)
4-digit-industry x product price*	-4.42	-7.32	-3.59	-4.56
	(1.14)	(2.04)	(0.75)	(1.12)
4-digit industry, plant sz polynm**	-2.06	-4.30	-2.80	-3.30
	(0.82)	(1.46)	(0.71)	(1.06)
Previous + other*** controls.	-1.95	-3.23	-1.36	-2.46
	(0.67)	(1.19)	(0.51)	(0.79)
Previous + Exporter, Foreign Ownership				

* seven categories of "prices charged for most products" (including "no response" category) fully interacted w/four digit industry. ** 6th order polynomial in plant employment. *** plant age, etc. -- see Table 2. Columns (2) uses as the instrumental variable predicted high school dropout share among immigrants who arrived 1980-86, predicted from 1970 locations of immigrants from 16 world regions. Columns (4) uses as the instrumental variable predicted high school dropout share among immigrants who arrived 1988-93. See text for details.

Table 6b. Impact on Number of "High-Tech" Machines Per Employee, 1993

	1993 N=4,757	
Controls	OLS	IV
	(3)	(4)
No Controls	-0.09	-0.12
	(0.03)	(0.04)
4-digit-industry	-0.05	-0.10
	(0.03)	(0.05)
4-digit-industry x product price*	-0.03	-0.08
	(0.02)	(0.03)
4-digit industry, plant sz polynomial**	-0.07	-0.11
	(0.03)	(0.05)
Previous + other*** controls.	-0.04	-0.09
	(0.03)	(0.05)
Previous + Exporter, Foreign Ownership		

Dependent variable is a count of "high tech" machines per employee, where machines include CAD/CAM/CAE, numerically controlled machines, marterials working lasers, pick and place robots, other robots, programmable controllers and computers used for control on factory floor. *, **, *** See Table 2. Column (2) uses as the instrumental variable predicted high school dropout share among immigrants who arrived 1988-93. See text for details.

Table 7. Impact of Change in Dropout/HS Eqivalent on Change in Number of Technologies in Use, 1988-93

Controls	OLS (N=1,474)	2SLS
	(1)	(2)
No Controls	-3.25	-7.40
	(4.10)	(11.41)
4-digit Industry, 1988	-1.12	-7.77
	(4.02)	(14.10)
4-digit Industry, 1988 and 1993	-1.59	-8.62
	(3.80)	(14.47)
Previous + #Techs in use, 1988	-2.25	-17.75
	(2.23)	(7.53)
Previous + #Techs planned, 1988	-4.18	-18.47
	(2.42)	(7.41)
Previous + Plant Size Polynomial*	-4.31	-17.90
	(2.37)	(6.43)
Previous + Other Baseline Controls	-2.99	-15.81
	(2.28)	(6.15)

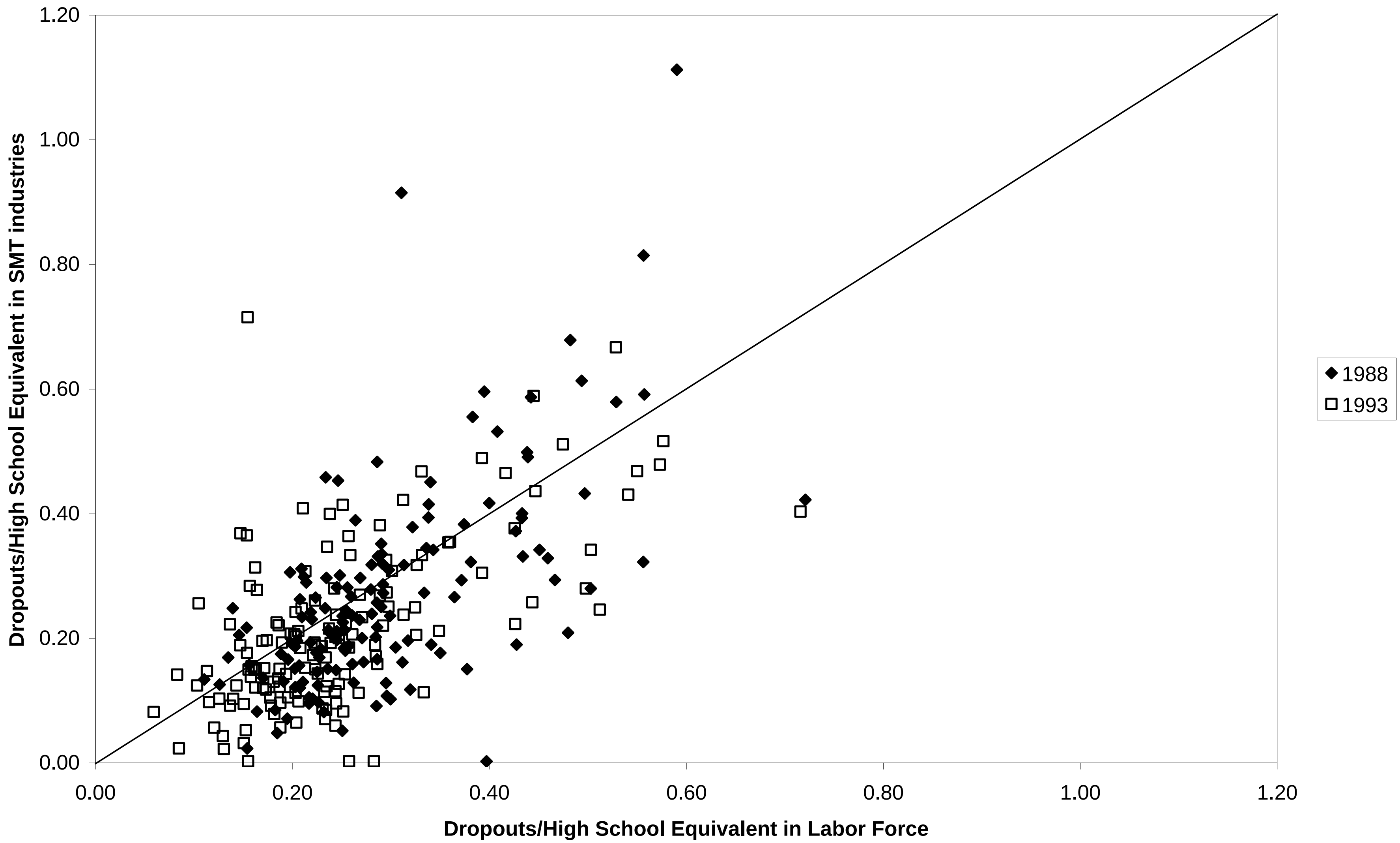
* 6th order polynomial in 1988 plant employment.
Instrument is predicted high school share dropout among immigrants who arrived in the U.S. 1988-93, predicted with 1970 metro area locations of immigrants from 16 world regions. See text for details.

Table 8. Specification Check: Are *Future* Changes Dropouts/HS Equiv Associated with Plans to Add Technology?

Controls	OLS	IV
No Controls	1.19 (1.21)	0.99 (2.32)
4-digit-industry	1.38 (1.18)	1.09 (2.27)
4-digit-industry x product price*	1.13 (1.25)	1.08 (2.40)
4-digit industry, plant sz polynom.	1.12 (1.22)	0.92 (2.23)
Previous + other baseline controls	0.82 (1.17)	1.24 (2.26)

Notes: See Table 3. Regressions use 1988 employment weights

Figure 1. Dropouts/High School Equivalent in SMT industries vs. Labor Force



Appendix Table A1. Impact of Overall Dropout Share on the Number of Technologies in Use, 1988 and 1993

	1988 N=6,571		1993 N=4,757	
Controls	OLS	IV	OLS	IV
	(1)	(2)	(3)	(4)
No Controls	-10.30	-13.09	-9.92	-8.04
	(3.40)	(7.65)	(2.78)	(4.57)
4-digit-industry	-7.14	-25.63	-10.45	-15.13
	(3.10)	(7.81)	(2.52)	(4.18)
4-digit-industry x product price*	-7.17	-24.49	-8.92	-13.63
	(3.05)	(7.61)	(2.07)	(3.45)
4-digit industry, plant sz polynm**	-3.52	-14.37	-6.45	-9.86
	(2.15)	(5.24)	(1.96)	(3.25)
Previous + other*** controls.	-3.45	-9.68	-2.96	-6.60
	(1.75)	(4.12)	(1.42)	(2.38)
Previous + Exporter, Foreign Ownership			-3.33	-7.87
			(1.43)	(2.43)

* seven categories of "prices charged for most products" (including "no response" category) fully interacted w/four digit industry. ** 6th order polynomial in plant employment. *** plant age, etc. -- see Table 2. Columns (2) uses as the instrumental variable predicted high school dropout share among immigrants who arrived 1980-86, predicted from 1970 locations of immigrants from 16 world regions. Columns (4) uses as the instrumental variable predicted high school dropout share among immigrants who arrived 1988-93. See text for details.