IMMIGRATION, SKILL MIX, AND CAPITAL-SKILL COMPLEMENTARITY*

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Abstract. Over the past thirty years, U.S. manufacturing plants invested heavily in automation machinery. This paper shows these investments substituted for the least-skilled workers and complemented middle-skilled workers at equipment and fabricated metal plants. Specifically, it exploits the fact that some metropolitan areas experienced faster growth in the relative supply of less-skilled labor in the 1980s and 1990s due to an immigration wave and the tendency of immigrants to regionally cluster. Plants in these areas adopted significantly less machinery per unit output, despite having similar adoption plans initially. The results imply that fixed rental rates for automation machinery reduce the impact that immigration has on less-skilled relative wages.

* This research was conducted while I had Special Sworn Status at U.S. Census Bureau's research data centers in Berkeley, CA and Boston, MA. Results and conclusions do not necessarily reflect the views of the Bureau of the Census. The paper has been screened to insure that no confidential data are revealed. I am grateful for the valuable feedback I received on this work from two anonymous referees and David Autor, Paul Beaudry, Michael Ben-Gad, Marianne Bitler, Clair Brown, Benjamin Campbell, David Card, Elizabeth Cascio, Kenneth Chay, Eric Edmonds, Andrew Hildreth, Larry Katz, David Lee, Nina Pavcnik, Albert Saiz, my former colleagues at the Federal Reserve Bank of Philadelphia, and seminar participants at the University of British Columbia, U.C. Berkeley, Society of Labor Economists Meetings, the IZA conference on International Migration, the University of Maryland, San Francisco Federal Reserve Bank, Drexel University, and Dartmouth College. Shannon Mail provided excellent research assistance. I alone am responsible for any errors.

A large body of research argues that new workplace machines, like computers, complement skilled labor, and that a sharp decline in their price in recent decades has increased relative demand for skilled labor in the U.S. labor market. While the view that "skill biased technical change" (SBTC) has increased wage inequality in the U.S. has considerable support, few natural experiments have verified technology-skill complementarity.[1] Instead, evidence for SBTC largely derives from associations between the use of new technology and the relative employment and wages of skilled workers, which some argue do not imply that recent technological change has had a large impact on the wage structure (e.g., DiNardo and Pischke [1997]).[2]

In light of the difficulty of finding random variation in technology adoption, this paper exploits shocks to the supply of skills to evaluate technology-skill complementarity. Specifically, it compares technology adoption rates across U.S. metropolitan areas with different shocks to the relative supply of high school dropouts induced by the recent wave of low-skilled immigration to the U.S. This immigration boom was substantial – immigrants' share of the labor force has climbed from 5 percent in 1970 to 15 percent today – and has contributed strongly to the slow growth in the supply of skills in the U.S. Immigrants have also persistently clustered into certain U.S. labor markets, so much so that one can predict recent skill mix changes in a market from long lags of immigrant density. This fact has been heavily used to assess the impact of immigration on the wages of native-born workers. Here it is instead used to assess how technology adoption responds to increases in the relative supply of low-skill labor.

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[1] A quasi-experimental approach is taken by Acemoglu and Finkelstein (2008), who show a change in the Medicare reimbursement formula which drove down the relative price of capital at Medicare-intensive hospitals was associated with increased relative employment of more-skilled (registered) nurses. They do not push the finding hard, however, as there was already a smaller differential trend towards hiring more RNs at Medicare-intensive hospitals before the change.

[2] Studies have used variation across workers (e.g., Krueger [1993]), plants (e.g., Dunne et al. [2004]), and industries (e.g., Autor, Levy, and Murnane [2003]). Using data very similar to the present data, Berman, Bound, and Griliches (1994) show that the skilled (non-production) wage bill share rose faster with greater computer and machinery investments. These associations do not always support SBTC. In a critique of Krueger (1993), Valletta (2006) shows that there is little association between computer adoption and wage growth across demographic groups.

The technologies studied in the present paper are not computers, but the types of automation machinery introduced into manufacturing in the past few decades and covered by the 1988 and 1993 Surveys of Manufacturing Technology (SMT) used in this study (see Table A.1). Manufacturing automation is particularly suited to this study because the high school dropouts in SMT-covered industries (SIC 34-38, which covers equipment and fabricated metal products), especially immigrants, are concentrated in labor-intensive assembly, welding, and other tasks that these technologies replace. As one early 1980s forecast of the likely impact of automation 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), using SMT data, found that plants using automation had a higher high-skill share in employment. They expressed doubts that the relationship was causal, however, as the same plants had a higher skill share well before they adopted the technology.[3]

Combining the SMT technology data with metropolitan area-level labor force data aggregated from Current Population Surveys and Censuses of Population, I find that plants added technology more slowly between 1988 and 1993 where immigration induced the ratio of high school dropouts to graduates to grow more quickly.[4] In addition, using a broader sample of manufacturing plants from the Census of Manufactures, I find that increases in low-skill relative supply are associated with slower growth in capital-labor and capital-output ratios. Consistent with the instrumental variable being valid, it is uncorrelated with the labor market conditions facing high school dropouts "pre-automation" (1980) and plants' automation adoption plans in 1988.

Absent other evidence, a remaining concern would be that these results were driven by open economy adjustments: immigration induces an area to shift to a more unskilled-intensive product

[3] Further, Luque and Miranda (2005) show the higher average wages paid at technology-intensive plants may derive from firm and worker unobservables.

[4] More precisely, this is the ratio of high school dropouts to high school "equivalents" (exactly 12 years of schooling plus half of those with 13-15 years of schooling). Similar results are found examining changes over 1980 to 1988.

mix (e.g., Hanson and Slaughter [2002]), resulting in factor price equalization, and what appears to be a response of technology use to skill mix shocks is in fact due to a shift to a less automation-intensive product mix. Inconsistent with this, controls for narrow industry, and within those, a proxy for the factor content of products (product price, suggested by Schott [2004]) do not weaken the relationship between technology adoption and skill mix shocks.[5] This reinforces other evidence that open-economy adjustments to immigration are small (e.g., Lewis [2004b]).

These results are consistent with automation machinery being a relative substitute for low-skill labor (and a relative complement for middle-skilled labor).[6] This implies fixed machinery rental rates buffer the relative wages of low-skill labor from the impact of shocks to their relative supply.[7] This paper's findings thus complement a leading explanation for why low-skill immigration has little impact on wages (Card [2009], discussed below).

I. Theory and Background

Nested constant elasticity of substitution (CES) specifications provide a flexible way to model production in general, and have become a common way to model capital-skill complementarity. Even limiting oneself to nested CES production functions there are a variety of ways to model capital-skill complementarity (Krusell et al., 2000).[8] The following setup was chosen to be consistent with basic facts about the level of complementarity between different labor types in general, and of how labor is used in manufacturing, the focus of this study, in particular.

At the most abstract level, manufacturing final output combines intermediate non-production and production outputs:

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[5] Also, relative wages vary systematically with relative supply, inconsistent with factor price equalization.

[6] Manufacturing automation thus has a different effect than the computerization of office work, which appears to raise demand for high-skill relative to middle-skilled labor (e.g., Autor, Katz, and Kearney [2006]).

[7] Rental rates are fixed under elastic supply, a maintained assumption of this analysis consistent with the fact that the markets under analysis -- metropolitan areas -- are small relative to the total market for automation machinery.

[8] Earlier work by Goldin and Katz (1998) used the nested CES production modeling approach to explore the historical evolution of capital-skill and technology-skill complementarity.

$$Q = \left(N^{\gamma} + P^{\gamma}\right)^{\frac{1}{\gamma}}$$

...where $\gamma \leq 1$ governs the elasticity of substitution between non-production (N) and production (P) outputs. Production output is a function of the employment of automation machinery (K_M), and two types of production labor, high-skill and low-skill or, to link it explicitly to the empirics below, high-school graduates (H) and high school dropouts (L):

$$(1)\quad P = A\left(K_M^{\theta} + L^{\theta}\right)^{\frac{\alpha}{\theta}} H^{1-\alpha}$$

Labor inputs are supplied inelastically. Other symbols in (1) represent parameters. A larger $\theta \leq 1$ defines a greater degree of substitutability between machines and unskilled labor, and $\alpha \in (0,1)$ is the low-skill aggregate's share in production. $\theta > \alpha$ is consistent with capital-skill complementarity. SBTC can be modeled as a decline in r, the price of K_M. Non-production output is:

$$(2)\quad N = C$$

C is the employment of a third type of labor, college-educated workers.[9] (2) is oversimplified: a more general and realistic model would nest C with office equipment including the personal

[9] It will be shown below (Table II) that college-educated labor is concentrated in non-production.

computer, say $N = \left(K_C^{\delta} + C^{\delta}\right)^{\frac{1}{\delta}}$. While important, these other forms of capital are not the focus of the current study, so I abstract away from them to simplify the math.[10]

Autor, Levy, and Murnane (2003) (ALM) use a model like (1) but make low-skill labor and computers perfect substitutes ($\theta = 1$), which they make clear is a simplifying assumption to make it easy to see that relative demand for L falls with the price of computers, r.[11] They also allow α to vary across industries, implying computerization will be more extensive in industries with higher pre-computer L-intensity (sectors with larger α), which their empirical analysis investigates.

Like ALM (and Caselli and Coleman [2001]), the present paper examines the impact that skill mix has on technology use, rather than the more commonly studied reverse relationship. Rather than look across industries (or countries), however, the present study looks across local labor markets in the U.S., arguing that historical patterns of immigration generate exogenous changes in local skill mix (described below). To be explicit, if K_M is supplied perfectly elastically at price r, and if $\theta > \alpha$ (a sufficient condition), then in equilibrium K_M responds positively to exogenous increases in the relative supply of H and C-type labor:[12]

[10] In the industries under study in this paper, as of 1993 (the last year of this study's data) only 17 percent of manufacturing equipment stock was in office equipment. More recent numbers are not much higher -- around 20 percent. (Net stocks of assets at current costs by industry from http://www.bea.gov/national/FA2004/Details/Index.html, accessed 1 October 2009). In contrast, in the economy as a whole office equipment represents about 31 percent of equipment capital ("Information processing equipment and software" figures in "Table 2.1. Current-Cost Net Stock of Private Fixed Assets, Equipment and Software, and Structures by Type," accessed via http://www.bea.gov/national/FA2004/SelectTable.asp. on 1 October 2009).

[11] When computers and low-skill labor are perfect substitutes, $r = w_L$, the low-skill wage. ALM also model workers' labor supply as driven by their comparative advantage in doing low- (in their model, "routine cognitive") and high-skill tasks, which implies that the low-skill share of total employment falls with the price of computers. Recent research argues that computers replace middle skill workers (e.g., Goos and Manning [2007]; Autor, Katz and Kearney [2006]), which are closer to what the "H" type workers in the present model correspond to. This is discussed further below.

[12] This expression was derived from setting the log differential of the first order condition for K_M to zero under the elastic supply assumption, i.e. demand for capital has no effect on its price, r. All results are for interior solutions.

$$(3)\quad \begin{aligned} d\ln\left(K_M/L\right) = & \frac{1-\alpha\left[1-(1-\gamma)(1-s)\right]}{\left\{\theta-\alpha\left[1-(1-\gamma)(1-s)\right]\right\}\omega+(1-\theta)} d\ln\left(H/L\right) \\ & + \frac{(1-\gamma)(1-s)}{\left\{\theta-\alpha\left[1-(1-\gamma)(1-s)\right]\right\}\omega+(1-\theta)} d\ln\left(C/H\right) \end{aligned}$$

where $\omega \equiv rK_M/\alpha P$ is K_M's share of the K_M-L nest in (1) and *s* is production's share of final output.

A negative relationship between the relative supply of low skill labor and the use of machinery is not unique to production functions that feature capital-skill complementarity. A key alternative is the types of production functions conventionally used in research on the labor market impact of immigration (for example, Card [2001]; Borjas [2003]). To make capital ignorable in estimation these studies typically specify output as separable in capital and labor; to be general say,

$$(4)\quad Q = \left[K_M^{\sigma} + f\left(L,H,C\right)^{\sigma}\right]^{1/\sigma}$$

where f(·) might be another CES nest. Capital is skill-neutral in (4), but an increase in the relative supply of low-skill labor lowers f(·) and makes K_M fall.[13] However, under (4) capital and output have the same proportional response to skill mix shocks: capital's share of output is fixed.[14] The present paper's model instead implies:[15]

$$(5)\quad \begin{aligned} d\ln\left(K_M/Q\right) = & \frac{(1-\omega)\left(\theta[1-\alpha s]-\alpha\gamma[1-s]\right)}{\left\{\theta-\alpha\left[1-(1-\gamma)(1-s)\right]\right\}\omega+(1-\theta)} d\ln\left(H/L\right) \\ & + (1-s)\frac{(1-\alpha\omega)(1-\gamma)-\left[(\theta-\alpha)\omega+(1-\theta)\right]}{\left\{\theta-\alpha\left[1-(1-\gamma)(1-s)\right]\right\}\omega+(1-\theta)} d\ln\left(C/H\right) \end{aligned}$$

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[13] In equilibrium, $r = \left[K_M^{\sigma} + f\left(L,H,C\right)^{\sigma}\right]^{1/\sigma-1} K_M^{\sigma-1}$ (first order condition), so at a given r, decreases in f make K_M fall.

[14] The first order condition (previous note) can be rewritten to show capital is a fixed share of output $rK_M/Q = r^{\sigma/(\sigma-1)}$.

[15] This expression subtracts the log differential for Q/L from (3), and then substitutes in (3) for dln(K/L).

(5) says that if $\theta > \alpha$, capital's share of output rises with the relative supply of high-school production workers; similarly, if $\theta > \gamma$ it also responds positively to the relative supply of college workers. (Both are sufficient conditions). The regressions below largely ask how various proxies for K_M respond to local skill mix shocks. (4) and (5) remind us that in order to be able to interpret any such relationship as coming from capital-skill complementarity, one must also show that output responds by a smaller amount to the same shocks.

Interestingly, if γ is positive (again, a sufficient condition),[16] capital responds more to the relative supply of high school than college workers: the coefficient on dln(H/L) in (5) is larger than the one on dln(C/H). The coefficient on dln(C/H) can even be negative under reasonable parameter values.[17] This may seem surprising in light of much of the literature which finds a strong positive association with college relative supply and computers. However, most manufacturing capital is used in production and employed by workers with less than a college degree. In addition, the model (and the data used, largely) exclude the office computers that college workers use. Including office equipment in the nest with C would likely reverse this implication.

I.A. Wages

This model also generally implies downward sloping relative demand for labor inputs. The expressions for relative wages in terms of labor mix are:

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[16] The necessary condition is $\gamma > -(1-\omega)\theta s/(1-s) - \alpha\omega/(1-\alpha)$.

[17] An increase in the relative supply of C can push down production's share of output. This leads to a reduction of K_M per output when $\gamma > \theta(1-\omega)/(1-\alpha\omega)$.

$$d\ln(w_H/w_L) = -\frac{(1-\theta)(1-\alpha\omega)[1-(1-\gamma)(1-s)]}{\{\theta-\alpha[1-(1-\gamma)(1-s)]\}\omega+(1-\theta)}d\ln(H/L) + \frac{\theta\omega(1-\gamma)(1-s)}{\{\theta-\alpha[1-(1-\gamma)(1-s)]\}\omega+(1-\theta)}d\ln(C/H) \quad \text{(6a)}$$

$$d\ln(w_C/w_H) = \frac{\gamma\alpha(1-\theta)(1-\omega)}{\{\theta-\alpha[1-(1-\gamma)(1-s)]\}\omega+(1-\theta)}d\ln(H/L) - (1-\gamma)\frac{(\theta-\alpha s)\omega+(1-\theta)}{\{\theta-\alpha[1-(1-\gamma)(1-s)]\}\omega+(1-\theta)}d\ln(C/H) \quad \text{(6b)}$$

(6a) and (6b) imply that the higher the substitutability between low-skill labor and automation, the less sensitive relative wages will be to local changes skill mix. For example, in ALM's simplifying case ($\theta = 1$), wages are insensitive to changes in H/L. In essence, the fixed price (elastic supply) of capital buffers the impact of skill mix on the relative wages of factors that capital relatively substitutes for; in the extreme ($\theta = 1$), it pins down relative wages. In contrast, if capital supply were inelastic, wages would respond as if capital were skill neutral, i.e., $\partial\ln(w_H/w_L)/\partial\ln(H/L) = -1$ and $\partial\ln(w_C/w_H)/\partial\ln(C/H) = -(1-\gamma)$. Under same conditions as above, these are larger magnitude responses than in (6a) and (6b).[18] This and other wage implications are discussed further in the results and discussion sections below.

I.B. Distinguishing from Open-Economy Type Models

In addition to the skill-neutral model in (4), there is another model whose implications overlap with the model of capital-skill complementarity above. Beaudry and Green's (2003, 2005) (BG) model of "technological revolutions" (Caselli, 1999) emphasizes the impact the supply of factor inputs have on the decision to adopt a new technology. In a simple version of this model, a

[18] $\gamma>0$ and $\theta>\alpha$ are jointly sufficient for relative wages to respond less to relative supply under elastic capital supply.

new so-called "modern" production technique has a discretely higher skill requirement than an older "traditional" technique.[19] The higher skill requirement implies that use of the modern technique rises with the availability of skilled labor. This analog of what trade theorists call the "Rybczynski theorem" (e.g., Leamer, 1995) is shown graphically in Figure I. Unit isoquants of modern (labeled Q_M=1) and traditional (labeled Q_T=1) methods are shown in factor (H,L) space, along with the isocost line $1/w_H(r)$ to $1/w_L(r)$. The modern isoquant is up and to the left of the traditional one, indicating its greater skill-intensity. Full employment inside the so-called "cone of diversification" (inside the two expansion paths coming from the origin) is reached by producing with a combination of modern and traditional methods, as indicated by the vectors leading to the endowment point (H,L). An increase in the relative supply of less-skilled labor – moving from (H,L) to (H,L') – results in greater use of the traditional method of production. In short, this very different model of technological change also implies that increases in relative supply of skilled labor increases the use of the new technology.[20]

Figure I is identical to a simple version of a small, open economy model and so also helps to illustrate the potential confounding influence of changes in industry mix, or "open economy adjustments." In the standard interpretation Figure I, Q_M and Q_T represent different products. A local market faces elastic world demand for the two products, so changes in its factor mix are absorbed by shifts in product mix. What may appear to be a shift towards greater automation as the supply of skilled labor increases, therefore, might really be a shift to a more automation-intensive product mix (say, from "low tech" metal fittings to "high tech" machine tools). In the empirical analysis, therefore, it will be important to control for industry.

[19] This version is taken from Beaudry, Doms, and Lewis (2010) whose skill groups are college and non-college workers.
[20] Figure I does not include capital, but the modern technique is defined to be the one which uses automation more intensively.

Previous research directly examining the extent to which open economy adjustments absorb changes in factor mix in U.S. regions (e.g., Hanson and Slaughter [2002]; Lewis [2004a, 2004b]; Bernard, Redding, and Schott [2005]; Saad-Lessler [2005]) comes to mixed conclusions. The present study controls for industry in finer detail – four-digit SIC – than any of these previous studies. In some specifications, four-digit industry will be interacted with product price, which Schott (2004) shows captures differences in the factor content of products within four-digit industries.

Both BG and open economy model also predict that as long as skill mix does not become too extreme (stays inside the cone of diversification), wages are not, in the long run, affected by local skill ratios. In the model of capital-skill complementarity this factor price insensitivity result holds only under extreme parameter values ($\theta=1$). Thus, the response of wages can help rule out that the results are driven by open economy adjustments or a model like BG.

II. Data and Methods

The analysis examines the relationship between a manufacturing plant's use of automation machinery and the relative supply of less-skilled labor in its metro area. The primary measures of automation come from restricted-access microdata versions of the 1988 and 1993 Surveys of Manufacturing Technology (SMT), supplemented with information from the 1987 and 1992 Censuses of Manufactures. Each SMT polled a stratified random sample of around 10,000 manufacturing establishments with at least twenty employees in SIC industries 34-38 on the use of, plans for use of, reasons for use of (or for not using) seventeen categories of advanced manufacturing technologies.[21] These technologies (listed Appendix Table A.1) include processes used both in production and non-production activities, but most of the technologies are for use on

[21] The industries covered by the SMT – fabricated metal products, industrial machinery and equipment, electronic and other equipment, transportation equipment, instruments and related products – represent 43 percent of the manufacturing sector (value added or employment) in 1987 (U.S. Bureau of the Census [1989]).

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.

In the regressions, the dependent variable will be a simple count of the number of technologies in use by the plant, or the number added.[22] Although this summary potentially masks some interesting variation, a number of studies using these data, including Doms, Dunne, and Troske (1997) (DDT), summarized the data this way.[23] In addition, the principal component of seventeen technology dummies turns out to be almost equal to the simple count, which captures almost fourty percent of the variation in the use of individual technologies.

II.A. Sample and Weights

Though the SMT was a random sample, it was also a small sample, so some areas could be over- or underrepresented by chance. A report prepared for the Census Bureau that compared employment and plant counts in the SMT sample to the Census of Manufactures (and to the County Business Patterns) showed that the data were close to geographically representative, with some minor exceptions, such as there being "too few" California plants in the 1988 data (Lewis, 2006). The analysis uses sample weights constructed to reflect the geographic distribution of employment in the SMT universe. (See Data Appendix for details.) In practice, consistent with the report's finding that the raw data are geographically representative, weighting has little effect on point estimates, but enlarges the standard errors. Nevertheless, for the purpose of interpreting the results as the impact on technology use "at the average worker's plant," weighted results are presented.

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[22] 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.

[23] Beede and Young (1998) found that the association between technology use and productivity, employment, and earnings vary by technology type, sometimes differing in sign. In contrast, I cannot reject that the impact of the high school dropouts/equivalent on the use of these technologies is uniformly negative.

Regressions are run across 143 metropolitan areas for which all the necessary data are available.[24] Table I shows the (weighted) means and standard deviations of all of the variables used in the regressions. Panel A shows the SMT variables discussed above. In 1988, the average employee in the SMT-universe in these cities was at a plant using six technologies. There is wide variation across plants in the use of technology; the standard deviation is nearly as large as the mean. More than ten percent of this variation is accounted for by variation across labor markets, even when holding constant industry mix.[25] The table also breaks down the technology use into its major categories (which sum to the total). The 1993 SMT survey also asked a separate question about the technologies added since 1988. Table I shows the average employee's plant added about three technologies, in line what they predicted they would add in 1988.

II.B. Skill Mix

The skill mix of each metropolitan area's workforce is estimated using Census of Population data and Current Population Survey (CPS) micro data for non-census years.[26] In particular, 1988 figures computed using stacked 1987-1989 CPSs, and 1993 figures computed using the 1992-1994 CPSs. Corresponding to the C, H, and L workers in the model above workers are divided, respectively, into college and high school "equivalents" and high school dropouts. College and high school equivalents, here defined by assigning one-half of workers with some college (1-3 years college) to be college graduates and half to be high school graduates, is a common way research on SBTC (e.g., Katz and Murphy [1992]; Autor, Levy, and Murnane [2003]) divides up workers.[27]

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[24] The biggest loss of metropolitan areas comes from the requirement that each area 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, which eliminates an additional 15 metropolitan areas.
[25] When city dummies are added to a plant-level technology use regression, the R^2 increases by more than 0.1.
[26] Specifically, the National Bureau of Economic Research's version of the Merged Outgoing Rotation Group files.
[27] 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.

The focus of this study is on the effect of changes in L/H -- high school dropouts per high school equivalent. Examining this skill margin has several motivations. First, it is the margin on which immigration to U.S. labor markets has its strongest influence, and a goal of this paper is to understand how immigrants are absorbed into U.S. labor markets. Second, it appears to be a skill margin relevant to the use of production-related automation technologies. Hunt and Hunt's (1983) survey of the potential impact of robotics, for example, talks about the loss of less-skilled jobs in favor of mostly vocationally trained workers and some engineers. Bartel et al. (2003) attempt to learn about the impact of new technologies on the skill requirements of production jobs through site visits to several plants in a variety of the same industries covered by the SMT. They found that new technologies increasingly require "soft" skills – communication and problem-solving skills – in addition to math, literacy, and to some extent computer skills which can be acquired in high school.

Third, differences in the occupational mix of workers by education argue for a focus on the high school education margin. Panel A of Table II shows the proportion of worker's hours in SMT-covered industries that were in selected occupations in 1990 by the education level and nativity of the worker.[28] The data usefully identify an occupation which directly involves modern manufacturing machinery: programmers and operators of computers and numerically controlled (CNC) machines.[29] These occupations, shown in the first row of Panel A of Table II, appear to be tiny, but census figures are likely orders of magnitude too small in light of how widespread CNC machines are (at 40% of plants in the SMT according to U.S. Bureau of the Census [1989]), and other survey evidence on the prevalence of CNC operators (e.g., Bartel et al. [2007]).[30] That aside,

[28] Calculations from the 1990 census of population. The sample used to compute the table was limited to workers residing in the geographic region covered by the regression analysis below.
[29] In the 1990 census, such programmers and operators are identified separately in occupation codes 233 and 714.
[30] The Bureau of Labor Statistics computes, from their Occupation Employment Statistics (OES) survey, employment by detailed occupation. According to this survey, there were around 190,000 CNC operators in 1999, which was well more than one percent of manufacturing employment. Bartel et al. (2007) find that CNC operators represent over 25 percent of production workers in the valve industry -- which could be exceptional -- in their 2002 survey. The problem

Table II still informs us about the relative propensity of different skill types to work as CNC operators: CNC operators are overrepresented among high school graduates and those with some college relative to those with both more and less education.[31] This suggests that these middle skilled workers might complement automation. In contrast, production inspectors, assemblers, and other occupations in the Panel A that seem likely to be displaced by automation are weighted much more heavily towards high school dropouts. 45% of native-born and 56% percent of foreign-born dropout (and only 23 percent of some college and 5 percent of college-graduate) workers' hours are concentrated in the top ten dropout occupations listed in Table II.

Panel A of Table II also shows that the top ten occupations of four-year college graduates, comprising 60 percent of the hours they work in SMT industries, are all non-production jobs. This fact motivated putting them in a separate production "nest" from less-educated workers in the model in Section I. Section I showed this production structure implies that the impact of college relative labor supply on automation could be small or negative.

Arguing against a focus on the relative supply of dropouts to high school equivalents is wage evidence that suggests that high school dropouts and graduates are close to perfect substitutes (e.g., Card [2009]; Goldin and Katz [2008]), which is consistent with the apparent similarity of the occupation mixes of native-born dropouts and high school graduates (though a Chi-squared test rejects that they are the same). In addition, one might expect college educated labor supply to be important in light of the association DDT found between the use of these technologies and college share at the plants in the SMT.

To gain further insight into how to the appropriate specification, Table III estimates cross section and first difference relationships between the number of technologies in use (or added) and a

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in the census of population, and to a lesser extent the OES, may be that so many production workers are lumped into miscellaneous "machine operator" occupations.

[31] These differences are statistically significant.

general specification of education mix: the metropolitan area's share of workers with high school, some college, and at least four years of college.[32] Areas with a larger proportion of workers with high school education or more have significantly more automated manufacturing plants. The magnitude of this association is largest for areas with a high relative supply of workers with a high school degree or some college education. The similarity of their coefficients in most of the columns of Table III, in fact, helps rationalize combining them into a single skill group. The coefficient on (four-year) college share is smaller than the other two, though is not statistically different. This implies the effect of the supply of four-year college graduates relative to high school graduates is small or even negative, consistent with equation (5). The remainder of the paper thus focuses on providing stronger evidence that the impact of the relative supply of dropouts to high school equivalents may represent a causal effect. Identification issues are discussed in the next section.

Panel B of Table II also shows that foreign-born dropouts are well represented in the industries covered by the SMT: 9 percent foreign-born dropouts' working hours were in SMT-covered industries in 1990, which compares to 10 percent for native-born. The analysis will take advantage of differences in the change in skill mix across metropolitan areas that can be predicted by historical patterns of immigration. The fact that immigrants are well represented in these industries suggests it is feasible that immigration affected skill ratios in these industries. Importantly, immigrants also appear to work in similar occupations as native-born dropouts (Panel A).

II.C. Identification

In order to identify an effect on machine use consistent with theory above, I need to observe random shocks to skill supply where wages and machinery use adjust freely; and to observe any changes in machine use before either worker mobility or open economy adjustments -- shifts in

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[32] The estimates control for four-digit industry effects which have little impact on the estimates, but are important theoretically. They are weighted using the sample weights described above.

product mix -- re-equate wages with other markets.[33] The assumption that machinery's supply is elastic, or its price is fixed, is a maintained assumption which seems plausible when, as here, metro areas are the unit of analysis, as each is a small part of the national demand for capital. Shifts in product mix are at least partially observable and accounted for by controlling for industry mix. Nevertheless, the variation used in Table III may not represent supply shocks. Forces which raise less-skilled relative wages – such as a demand shock in sectors outside manufacturing – would both attract low skill workers and encourage labor-replacing technology adoption. To address this, I construct an instrument for changes in dropouts per high school equivalent using the impact that persistent, geographically concentrated flows of immigrants have had on the skill mix of U.S. cities.[34] If this variation represents labor supply shifts, it allows identification of the combination of parameters outlined in the equations in Section I.

Let $(L/H)_c$ represent dropouts per high school equivalent in city c. What immigrant arrivals ("I" superscript) contribute to changes in this skill ratio, ignoring other changes in the workforce, is:

$$(7)\quad \Delta(L/H)_c \approx \frac{(L/H)_c^0 H_c^0 + (L/H)_c^I H_c^I}{H_c^0 + H_c^I} - (L/H)_c^0 = \frac{H_c^I}{H_c^0 + H_c^I}\left[(L/H)_c^I - (L/H)_c^0\right]$$

$(L/H)_c^0$ is *c*'s pre-immigration skill ratio. (7) says that to raise a city's less-skilled relative supply, immigration must both make up a substantial fraction of the city's workforce ($H_c^I/(H_c^0 + H_c^I)$ is large) and be more unskilled than the city's existing workforce ($(L/H)_c^I - (L/H)_c^0$ is positive).

As the locations of recent immigrants could also be endogenous, (7) cannot be used as an instrument. Instead, the instrument takes advantage of the strong tendency of new immigrants to

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[33] These conditions for identification mirror Card (2009).

[34] I am grateful to an anonymous referee for the formulation of the instrument described below.

settle into existing "enclaves" of immigrants from the same part of the world (e.g., Bartel [1989]). Since Altonji and Card (1991), researchers have taken advantage of this fact to construct instruments for immigration flows based on lagged immigrant stocks. The argument for this type of instrument's validity is that the persistence of regional immigration patterns derives from new immigrants' preference to resettle with family – and much of U.S. immigration is "family-based" – or to be in a culturally familiar environment.[35] Specification tests will be performed below.

In this paper, where immigrants settled in 1970 is used to predict where they will settle in the 1980s and 1990s. Let g = 1…G index country-of-origin groups partitioning all immigrants, with H^{Ig} and L^{Ig} the number of high school and dropout immigrants from country *g* and who settled <u>anywhere</u> in the U.S. during our analysis period (computed using the "year of arrival" question in the 1990 and 2000 censuses of population -- see Data Appendix). They are apportioned to metro areas according to the 1970 settlement patterns, to "predict" recent immigration by city, specifically:

$$\text{(8a)} \quad \hat{L}_c^I \equiv \sum_g \frac{M_{gc,1970}}{M_{g,1970}} L^{Ig}$$

$$\text{(8b)} \quad \hat{H}_c^I \equiv \sum_g \frac{M_{gc,1970}}{M_{g,1970}} H^{Ig}$$

Public-use 1970 census data are used to estimate $M_{gc,1970}/M_{g,1970}$, the share of the immigrant stock from country *g* living in metropolitan area *c* in 1970 regardless of skill level. This captures the idea of the immigrant enclaves. The instrument replaces actual immigrant counts in (7) with (8a) and (8b):

[35] For example, Gonzales (1998) finds that wages are lower and rents are higher in heavily Mexican markets, consistent with the presence of other Mexicans being an "amenity" valued by Mexicans.

$$(9)\quad Z_c \equiv \frac{\hat{H}_c^I}{H_c^0 + \hat{H}_c^I}\left[\left(\hat{L}/\hat{H}\right)_c^I - \left(L/H\right)_c^0\right]$$

Table IV shows the first stages for the two periods that will be analyzed: columns (1) and (2) are for 1980-88, and columns (3) and (4) are for 1988-1993.[36] If immigrants settled in the same cities in the same proportions as they did in 1970, and if other changes in workforce composition were unrelated to the instrument -- if there is little offsetting "native flight" -- then the first stage coefficient is one. For 1980-88 the coefficient is larger than one, reflecting that, due to data limitations, immigration flows are measured 1980-86 instead of 1980-88.[37] For 1988-93 the coefficient is indistinguishable from one, consistent with identifying labor shocks that have not dissipated by intercity mobility.

To be consistent with specifications estimated below for 1980-88, and to rule out the first stage derives from cross-sectional skill mix differences, columns (1) and (2) also include a control for dropouts per high school equivalent in 1980. This control makes little difference in the first stage, and columns (5) and (6) show the instrument is virtually uncorrelated with high school dropout share in 1980. Though perhaps surprising, as late as 1980 cities which now have large proportions of unskilled immigrants, like Los Angeles, had not yet had enough immigration to make them particularly unskilled; only after the large wave of immigration in the 1980s did high-immigration cities become more unskilled than low immigration cities.

The possibility that the instrument's correlation with unskilled labor share reflects long-run differences in growth in relative demand for unskilled labor cannot be completely ruled out. For example, Mexicans – a key driver of this instrument – may have chosen to settle in cities with high

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[36] Like the technology regressions, the first stage regressions are weighted by an area's manufacturing employment in the universe covered by the SMT (in SIC 34-38 and with at least 20 employees).

[37] The year of arrival question is reported in categories in the 1990 Census. The coefficient could also be larger than one if native- and foreign-born inter-city migration favors the same cities (Card and DiNardo, 2000).

potential for growth in demand for unskilled labor, anticipating having relatives join them in the future. However, Mexican enclaves are, for the most part, clustered near the border, suggesting distance from Mexico, not demand, might be the main reason for their location. Also, columns (2) and (4) show the instrument has little correlation with measures of labor market conditions facing high school dropout immigrants in 1980. I show below the instrument is also uncorrelated with plants' technology investment plans.

III. Results

Estimates of the relationship between the number of technologies added and the change in dropouts per high school equivalent between 1988 and 1993 are shown Panel A of Table V. [38] Both ordinary least squares (OLS) and instrumental variables (IV) estimates with no additional controls are noisy but consistent with a negative effect. Column (3) and (4) adds controls for detailed industry, dividing SMT plants into 161 four-digit industries. Though industry effects explain quite a bit of the cross-plant variation in technology adoption, their inclusion only strengthens the relationship with skill mix. Put another way, even within narrow industries, the adoption of automation technology negatively covaries with increases in dropouts per high school equivalent, inconsistent with (though not ruling out) factor price equalization.

As noted above, unobserved factors which raise low skill wages may both attract low skill workers and increase the use of labor-saving technology, biasing OLS estimates of the slope towards zero. Consistent with this, IV estimates are larger, which could also be due to measurement error attenuation of the OLS estimates. Section IV further discusses differences between OLS and IV.

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[38] Standard errors are computed to be robust to arbitrary error correlation among plants in the same metropolitan area.

As a test of the validity of this estimation procedure, panel B replaces the dependent variable with one from the 1988 survey, which asked plants how many technologies they planned to add over the next five years. It would cast serious doubt on a causal interpretation of these relationships if future changes in skill mix depressed plans to add technology. In fact, there is no such relationship. Coefficient estimates are insignificant, and even relatively small negative values are ruled out by these estimates.[39]

The 1993 technology added question appears to captures changes in technology use over the 1988-93 period well.[40] Unfortunately, there is no similar question in the 1988 survey. In order to analyze the period before this, I take advantage of the fact that the machines covered by the SMT were hardly used before the early 1980s (*American Machinist*, 1983), which means that the level of use is roughly equal to the change in technology use since 1980. So let T_{ct} represent the number of technologies in use in area *c* in year *t*, and Δ_{80} denote the change in a variable since 1980. Decomposing $(L/H)_{ct} = \Delta_{80}(L/H)_{ct} + (L/H)_{c,80}$ one can estimate:

$$(10)\ \ T_{ct}(\approx \Delta_{80}T_{ct}) = \alpha + \phi_1\Delta_{80}(L/H)_{ct} + \phi_2(L/H)_{c,80} + \varepsilon'_{ct}$$

If technology use was limited in 1980, ϕ_1 captures the relationship between changes in skill mix and changes in technology use 1980-88.

[39] It is fair to ask how accurately plant managers actually forecast their five-year investment plans. In the admittedly non-random sample of plants available in both the 1988 and 1993 surveys, a regression on the actual number technologies added on the forecast produces a coefficient of 0.21 (standard error 0.10). So plant managers have some ability to forecast, but it is not tremendous. On the other hand, if plant managers themselves do not make very accurate forecasts of future investments, it seems unlikely that foreign workers settle in markets in anticipation of them.

[40] A regression of the change in the numbers of technologies in use on the "technologies added" variable (again in the sample of plants available in both 1988 and 1993) produces a coefficient of 0.65 (with a standard error, clustered on metropolitan area, of 0.07). Direct first difference estimates 1988-93 are negative but uninformative because of large standard errors, though unweighted estimates are significant at the 10% level.

Estimates of (10) are shown in Table VI. Both OLS and IV estimates are highly significant, and similar in magnitude to Table V. Detailed controls for industry, added in columns (3) and (4), again do not weaken the relationship. To address the possibility that even four-digit industries may not fully absorb heterogeneity in the automation-intensity of the products, columns (5) and (6) control for four-digit industries interacted with the price of products sold by the plant, as suggested by Schott's (2004) finding that that a product's unit value is highly related to its factor content.[41] These controls are quite powerful, absorbing half of the variation in technology use across plants. Nevertheless, the influence of local skill supply is robust to within-industry product quality controls. So while it is still possible to argue product heterogeneity actually drives the relationship – i.e. that markets with low skill labor have a less technology-intensive product mix not fully captured by these controls – given how little impact these controls have on the estimates, this argument requires that these controls capture almost none of the variation the technology-intensity of products across markets, despite the fact that they capture a lot of variation in technology use across plants.

The SMT contains a number of other plant characteristics which might be added as controls (U.S. Department of Commerce, Bureau of the Census 1989, 1994). Most of these variables have little relationship with technology use and have little effect on the results.[42] Dunne (1994) shows, for example, there is little relationship between a plant's age and its use of technology. The main predictor of technology use he could find among the SMT variables was plant employment – larger plants use more technology. It is not entirely clear that a plant's size should be controlled for: a plant's size may be endogenous response to the technology choice. Nevertheless, columns (7) and (8) add the natural log of a plant's employment (from the prior-year CM) as a control. With this control added, one continues to find a significant, albeit reduced in magnitude, relationship between dropout share and technology use.

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[41] There are six product price categories. In addition, I treat non-response as a separate category.

[42] In an earlier version of this paper I confirmed that the SMT controls have little effect on the results.

III.A. Machinery and Output

The SMT is useful for measuring the use of specific types of machines which are likely to be highly substitutable for low-skill labor, but the sample is small. A less refined but continuous measure of capital intensity, the book value of machinery per worker, is available in a much larger survey, the Census of Manufactures (CM). If manufacturing machinery broadly complements mid-skilled labor and substitutes for less-skilled labor, exogenous increases in the relative supply of less-skilled labor should reduce capital per worker.[43] However, Section I showed that such a response is not sufficient to demonstrate capital-skill complementarity; a necessary condition is that output is less responsive in proportional terms than capital to the same skill mix changes.

Panel A of Table VII shows estimates in which the dependent variable is the change in the natural log of the (book) value of machinery per employee, pooled from 1987 and 1992 CMs, which is first regression-adjusted to take out the effects of four-digit industry.[44] OLS estimates are insignificant, but IV estimates are significant and large. To confirm that these and earlier results derive from capital-skill complementarity, Panel B shows estimates where the dependent variable is the natural log of output (value added) per worker. In neither OLS nor IV is there a statistically significant relationship between dropouts per high school equivalent and output. In addition, the proportional response of machinery per worker and the SMT technologies is uniformly larger than the proportional response of output. Dividing earlier coefficients by the mean number of technologies in use, the proportional response is between 1.0 and 2.0. This is much larger than the estimated proportional output response in Panel B, consistent with capital-skill complementarity.

[43] Griliches (1969) was the first to provide evidence of capital-skill complementarity using regional data from the CM.
[44] The sample is all plants in the CM with at least 20 employees, which is the universe for the SMT and CM. For a handful of plants in each year the book value of machinery is missing. I imputed machinery values at these plants from industry-specific estimates of a log-linear relationship with total shipments (estimated using the sample of reporting plants and four-digit industry); if that was not available, the mean value of machinery per employee in the plant's metropolitan area was assigned to the plant. Dropping these plants has little effect on the results, most likely because there are so few of them. The imputation procedure was used only because the Census Bureau frowns upon small changes in sample between specifications run with restricted access microdata. (Their concern is it might indirectly disclose information about an individual plant.)

III.B. Wages

The model of capital-skill complementary described in Section I also has wage implications that help distinguish the results so far from open-economy adjustments, or Beaudry and Green's model of a "technological revolution." The main model predicts relative wages fall with relative supply (equations (6a) and (6b)), while open economy adjustments and the revolutions model predict skill mix shocks have no long-run impact on wages (unless skill mix becomes extreme).

Table VIII estimates the relationship between changes manufacturing wages and changes in dropouts per high school equivalent, with IV estimates in Panel A and OLS estimates in Panel B. In columns (1)-(4) the dependent variable is the adjusted ln wage gap between dropouts and high school completers. Specifically, it is the change in τ_c from survey-year specific estimates of:

$$\ln w_{ic} = \delta_c + \tau_c 1[DO_{ic} = 1] + \beta' X_{ic} + \mu_{ic}$$

where $\ln w_{ic}$ is the natural log of the hourly wage of person *i* in metro area *c*, which is regressed on area dummies (δ_c), area dummies interacted with a high-school dropout dummy ($1[DO_{ic} = 1]$), and individual covariates, X_{ic}.[45] This regression includes only manufacturing workers with 9-12 years of education who are employed, have at least one year of potential experience (age - years of education - 6), are 20-65 years old, and earn wages between $2 and $200 in 1999 dollars.

[45] A quadratic in years of schooling, a quartic in years of potential work experience (age-education-6), a post-1950 cohort dummy and its interaction with years of education -- a specification suggested by Lemieux (2006) -- plus dummies for gender, black and their interaction. The post 1950 cohort dummy and interaction attempt to capture the effect of the slowdown in the growth in educational attainment for cohorts born after 1950 on returns to education, also noted in Goldin and Katz (2008).

Column (1) estimates come from stacked 1987-89 ("1988") and 1992-1994 ("1993") Current Population Surveys.[46] The OLS estimate of the relationship with high school dropouts per high school equivalent is positive, and though the IV estimate (using the same instrument as before) is negative, both estimates are very imprecise. The CPS is simply too small a wage sample to get reliable estimates of changes in average wages at the metropolitan level. In addition, it is not possible to separate out native-born workers in the CPS. To address both problems, estimates in column (2)-(4) use data from five percent public-use files of the 1980, 1990, and 2000 Censuses of Population for the same 143 metro areas.[47] Since those estimates include two decadal changes (1980-1990, 1990-2000), they also include a decade dummy as a control. Column (2) shows a significant, negative relationship between the relative supply and wages. Column (2) includes foreign-born workers, and so may be biased down by compositional changes associated with immigration. However, when foreign-born workers are dropped, in column (3), instrumental variables estimates are similar in magnitude.

Equations (6a) and (6b) have additional testable implications not discussed above. (6a) says that the relative supply of college-educated labor has a positive association with low-skill relative wages, as college labor complements non-production inputs. So column (4) is the same as column (3), but adds a control for college equivalents per high school equivalent. In the IV estimate, the coefficient on college relative supply is positive and the coefficient on dropout relative supply remains negative, but both estimates are imprecise.[48] (6b) says that college relative wages ought to

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[46] In the 1987-1989 data, anyone who reports attending and completing twelve years of education, or who reports attending but not completing thirteen years of education, is counted as a high school completer. In the 1992-1994 data, only those who report highest grade completed as "High school graduate, diploma or GED" are counted as high school completers. Those with less education (including "12th grade, no diploma" down to completed nine years, or attended ten years, in 1987-89, or completed ninth grade, in 1992-94) are high school dropouts.

[47] In the 1980 census, dropouts and high school completers are defined as in the previous note for the 1987-89 CPS. In the 1990 Census, they are defined the same as in the 1992-94 CPS. In the 2000 Census the definition is similar to 1990, though the education category "High school graduate" drops the reference to "diploma or GED."

[48] The instrument is constructed like to (9), but uses a version of (8a) with counts of college equivalents by country of origin and changes 1990-2000 are predicted from 1980 settlement patterns. The first stage F-statistic is 14.82.

respond negatively to college relative supply (and positively to dropout relative supply). Though not as obvious, under likely parameter values it also says that the response of college relative wages to own relative supply is larger than for dropouts.[49] The data support these predictions as well. Column (5) replaces the dependent variable with the adjusted college-high school wage gap, similarly estimated.[50] Consistent with this, the IV estimate has a positive coefficient on dropout relative supply and a negative one on college relative supply, and the magnitude of the own supply effect is larger for college graduates. The latter remains true when converted to elasticities: at mean skill shares (in 1990, roughly .3 for dropouts/high school equivalent and .9 for college/high school equivalent), the inverse elasticity is .08 (=.3*.277) for dropouts/high school, and .55 (=.9*.613) for college/high school. These estimates are imprecise -- neither is distinguished from zero at the 10% level -- but both are close to what Card (2009) estimated using a similar approach and what Goldin and Katz (2008) estimated using post-1949 aggregate data.

IV. Discussion

Throughout the paper, IV estimates of less-skilled labor's impact tend to be larger in magnitude than OLS estimates. When wages are the outcome (Table VIII) this seems sensible – wages partly reflect local differences in labor demand which likely influence where workers choose to live. This story is also consistent with IV estimates being larger than OLS estimates when technology use is the dependent variable. Third factors that drive up low-skill relative wages may

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[49] As long as $\gamma < \frac{(\theta - \alpha s_g)\omega + (1-\alpha\omega)(1-\theta)(1-s_g) + \alpha\omega(1-\theta)}{(\theta - \alpha s_g)\omega + (1-\alpha\omega)(1-\theta)(1-s_g) + (1-\theta)}$. This condition fails if γ is very close to 1 which, implausibly, would say that production and non-production outputs are highly substitutable. I do not heavily emphasize this claim, however, as the model in Section I excluded forms of capital which may be important for C-types' wages.

[50] Using individual-level data on those with exactly twelve and exactly sixteen years of education, I estimated, separately by year, $\ln w_{ic} = \tilde{\delta}_c + \tilde{\tau}_c 1[CG_{ic} = 1] + \tilde{\beta}' X_{ic} + \tilde{\mu}_{ic}$ where $[CG_{ic} = 1]$ is an indicator for the college group. The demographic controls in X_{ic} are as before except the control for the quadratic in years of education is dropped (since education only takes on only one value per skill group). The dependent variable in column (5) comes from time-differencing the year-specific coefficients $\tilde{\tau}_c$.

both attract low-skill workers and encourage low-skill replacing technology adoption, biasing OLS estimates of the impact of skill mix on technology adoption (and wages) towards zero. In addition, measurement error in skill mix may attenuate OLS estimates, and general changes in skill mix may have a smaller impact than immigration-induced ones.[51]

Estimates in Table VIII imply a large elasticity of substitution between dropout and high school graduate labor. For example, IV estimates imply an elasticity of about ten. This is typical of research on the local labor market impact of immigration, or so-called "area studies," though studies which analyze immigration's impact using larger geographic units, like Borjas (2003), tend to find a larger impact (see Longhi et al. [2005]). Many papers try to explain <u>why</u> the estimated local labor market impact of immigration is so small. How does the present paper relate to those claims?

One claim is that native outflows offset the impact of immigration on skill mix in local labor markets (Borjas, 2006).[52] This should not bias the results in the present paper, which examines total skill mix changes directly, instrumented with forecasts of immigration. Aydemir and Borjas (2010) show measurement error in local immigration shares can severely attenuate estimates of immigration's impact on wages in area studies. Classical measurement error should not attenuate IV estimates in the present paper as the instrument comes from an independent data source.[53]

Open economy models say local markets could adjust to low-skill immigration with limited (in the extreme, zero) wage impact, because they can adjust their product mix without affecting prices. Inconsistent with this interpretation, the use of machinery varies systematically with the availability of low-skill labor within industries more detailed than have been available in previous

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[51] Immigrant high school dropouts might have a larger impact on the relative supply of manual labor than native-born high school dropouts (Peri and Sparber, 2009). Also, because of chain migration, plant managers in areas with current inflows may expect continued growth in the availability of low-skill labor, further reducing their demand for automation.
[52] In contrast, Card and DiNardo (2000) find no evidence of a native flight response. Peri and Sparber (2010) argue Borjas's (2006) approach is biased towards finding a displacement effect where none exists.
[53] Estimates of the impact of immigrants on wages could also be small because immigrants natives with the same observable skills are imperfect substitutes (Cortes, 2008; Ottaviano and Peri, 2008). This is consistent with the incomplete (though large) occupational overlap between native- and foreign-born dropouts in Table II.

studies evaluating open-economy models across U.S. regions and, within those, a proxy for product factor content suggested by Schott (2004).

Most prominently, Card (2009) claims a key reason the estimated impact is small is that dropouts and high school graduates are near perfect substitutes.[54] When skill groups are properly specified, he argues, estimates do not vary by geographic level (for example, Card's [2009] local estimates are close to Goldin and Katz's [2008] aggregate estimates). The wage evidence in Table VIII, though noisy, is consistent with this. However, the present paper offers another interpretation of the near-zero wage response for dropouts: rather than being driven by the high substitutability of dropouts and graduates in production per se, it appears to be partly driven by the substitutability of dropouts for another factor -- machinery -- whose rental rate is likely insensitive to local labor market shocks.[55] More simply, dropouts and high school graduates are less substitutable than wage data indicate, a possibility that has been missed by the immigration literature's focus on skill-neutral production. To be clear, for many purposes the reduced form wage response is of interest; this paper offers a refinement of its interpretation.[56]

Finally, these estimates say manufacturing automation complements middle- relative to low-skilled workers, which is perhaps surprising in light of occupational evidence suggesting that computerization reduces demand for middle-skilled workers (Autor, Katz, and Kearney 2006, 2008; Goos and Manning, 2007). However, production automation may have a different impact than office computing technology that is the focus of these studies. Notably, employment of computer-controlled machine operators -- who typically have less than four-year college degree (Table II) -- grew 8.6 percent during the most recent expansion (2002-2008) despite the overall decline in

[54] The other key reason is that immigration has little impact on the relative supply of college labor. For a different view of the substitutability of dropouts and graduates, see Ciccone and Peri (2005).

[55] So if one wished to continue to argue that estimates of immigration's impact on wages is larger in the aggregate, a less elastic capital supply at the aggregate level would allow it. This argument is, however, inconsistent with Ottaviano and Peri's (2008) evidence that capital supply is elastic over a fairly short time frame even in the entire US aggregate.

[56] Complementarity between computers and college labor relative to middle skilled labor could also lead wage evidence to overstate the substitutability of college- and non-college workers, though that is not explored in the present paper.

manufacturing.[57] Thus, some recent technological change appears to benefit sufficiently skilled non-four-year college graduates as well.

IV. Conclusion

Researchers have argued for some time that diffusion of computer-based technologies raises relative demand for skilled labor (Krueger, 1993). A difficulty facing this research has been that the evidence supporting it is largely descriptive, based on associations between technology use and skill across plants or industries, leaving results vulnerable to the criticism that the association is not causal (DiNardo and Pischke, 1997). This paper confirms the existence of a form of capital-skill complementarity by showing that the response of manufacturing capital, output, and wages to changes in local skill ratios induced by immigration are consistent with it. Specifically, it finds manufacturing automation complements middle-skilled workers relative to low-skill workers.

What this paper interprets as differences in production technique may be differences in product mix below the observed level of industry detail (four-digit SIC). However, controlling for a proxy for product quality interacted with four-digit industry, which is highly correlated with cross-plant differences in technology use, has little effect on the results. This is stronger than previous evidence that shifts in product mix play little role in accommodating regional factor supply shocks.

Finally, recent empirical investigations of the labor market impact of immigration uniformly interpret their findings assuming capital is skill-neutral and ignorable in estimation (e.g., Card [2001]; Borjas [2003]). A model of capital-skill complementarity consistent with the empirical evidence in this paper shows that investments in automation induced by immigration reduce the impact immigration has on wages.

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[57] Archived OES data on http://www.bls.gov/oes/oes_arch.htm, accessed on May 21st, 2010. Production employment fell by 7.5 percent during the same period according to the survey.

Appendix A: Data Appendix

Surveys of Manufacturing Technology

The primary measures of automation used in this analysis come from restricted access microdata versions of the 1988 and 1993 Surveys of Manufacturing Technology (SMT), supplemented with information from the 1987 and 1992 Census of Manufactures. Each SMT polled a stratified random sample of around 10,000 manufacturing establishments with at least 20 employees in SIC industries 34-38 on the use of, plans for use of, reasons for use of (or for not using) 17 categories of advanced manufacturing technologies listed in Table A.1.

The analysis uses sample weights constructed to reflect the geographic distribution of employment in the SMT universe. These weights were constructed in two-digit SIC industry by employment class size (20-99, 100-499, 500+) by metropolitan area strata.[58] The weights are equal to total employment in the strata – measured with the prior year (1987 or 1992) Census of Manufactures – divided by the number of plants in the SMT in the strata.

Construction of the Instrument

The analysis examines changes in machine use 1988-93 and 1980-88. The H^{Ig} and L^{Ig} in (8a) and (8b) are computed using the "year of arrival" question in the 1990 and 2000 censuses of population. While these figures may understate migration during the period because some migrants will have returned home by the time of the census, they have the advantage of being broken out by education level, which is necessary for the construction of the instrument. Appendix Table A.2. lists the 16 world regions – the "g" index in (8a) and (8b) – used to construct the instrument, and columns (1) – (4) lists the number of dropout and high school equivalent immigrants arriving during the periods: 1980-86 -- the best available proxy for 1980-88 and 1988-93.

The instrument apportions these immigrants to the metropolitan area locations of immigrants from the same part of the world in 1970. For example, the top cities where the largest and most unskilled recent immigrant group, Mexicans, lived in 1970 include Los Angeles (32%), Chicago (7%), Houston (4%), El Paso (4%), and Anaheim (4%). The instrument predicts these cities will experience faster growth (in practice, slower declines) in dropouts per high school equivalent. These and all the rest of the $M_{gc,1970}/M_{g,1970}$ figures needed to construct (8a) and (8b) were constructed from the 1970 census public use five and fifteen percent county group files. In the five percent file, foreign-born are defined as non-citizens or naturalized citizens born outside the U.S. The citizenship question is unavailable fifteen percent file, so foreign-born are defined to be those born outside the U.S. and whose parents are also both born outside the U.S. The figures from each file are very similar. 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). For the purpose of defining metro areas, the June 30, 1990 county composition of metropolitan areas was used.[59]

[58] The strata used in the original design of the SMT were three-digit industry by those class sizes.

[59] As described at http://www.census.gov/population/www/estimates/pastmetro.html.

Appendix Table A.1. 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). *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."
   FMS – "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. Automated 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)

Appendix Table A.1. (Continued)

IV. Automated 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).

Appendix Table A.2. Origin and Skill Mix of Recent Immigrants Used to Construct the Instrument

Origin Region	1980-86 (for 1980-88)*		1988-93**		Dropouts/High School Equivalent	
	Dropouts	High School Equivalents	Dropouts	High School Equivalents	1980-86	1988-93
	(1)	(2)	(3)	(4)	(5)	(6)
Mexico	606,350	140,363	595,908	213,935	4.32	2.79
Other Central America	189,709	84,175	148,979	68,079	2.25	2.19
Cuba	49,395	27,220	13,088	10,796	1.81	1.21
SE Asia/Pac. Island	87,392	82,057	74,559	75,024	1.07	0.99
China, HK, Singapore	44,391	47,728	36,475	37,774	0.93	0.97
Caribbean	108,023	94,748	77,723	93,878	1.14	0.83
Southwestern Europe	22,456	15,394	7,513	9,948	1.46	0.76
India, Pakistan, Centr Asia	19,091	35,813	17,631	32,200	0.53	0.55
South America	63,183	93,951	43,262	80,666	0.67	0.54
Turkey, N. Africa, Mid. East	11,740	28,403	9,737	23,134	0.41	0.42
Other Africa	7,945	25,174	10,910	32,211	0.32	0.34
Philippines	22,410	55,195	14,479	45,826	0.41	0.32
Russia & Eastern Europe	18,840	39,997	24,141	79,814	0.47	0.30
Northern Europe & Israel	5,783	23,446	4,603	18,768	0.25	0.25
Korea & Japan	19,242	54,887	7,458	30,929	0.35	0.24
Canada, Aust/NZ/UK etc.	12,296	43,202	6,388	34,404	0.28	0.19
All Recent Immigrants	1,288,246	891,751	1,092,854	887,381	1.44	1.23

Data Source: Calculated using the *1990 and **2000 five percent public-use Census of Population using census person weights. Only working-age (age 16-65) foreign-born not living in group quarters, with at least one year of potential work experience, and who report being in the labor force are included in the calculations. "High school equivalents" include respondents who report completing high school or receiving a GED, plus half of those reporting having attended college but not obtaining a four-year degree. Column (5)'s numbers are equal to column (1) over column (2); column (6)'s numbers are column (3) over column (4).

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Table I. Descriptive Statistics

	1988 Mean	1988 Std Dev.	1993 Mean	1993 Std. Dev	Range
A. Surveys of Manufacturing Technology					
# of Technologies in Use	6.01	(4.68)	6.20	(4.45)	0-17
I. Computer Aided Design	1.25	(1.06)	1.44	(1.01)	0-3
II. Fabrication & Machining	1.57	(1.52)	1.48	(1.38)	0-5
III. Automated Materials Handling	0.30	(0.61)	0.27	(0.56)	0-2
IV. Automated Inspection	0.61	(0.84)	0.59	(0.82)	0-2
V. Communcation & Control	2.27	(1.81)	2.42	(1.84)	0-5
# of Techs Added Since 1988			3.09	(2.76)	
# of Techs Plan to Add by 1993	2.85	(2.90)			
# of Plants	6,571		4,757		
B. Census and Current Population Survey (Metro Area-Level Variables)					
Dropouts/H.S. Equivalent	0.30	(0.11)	0.27	(0.13)	
Change 1980-88	-0.16	(0.09)			
Change 1988-93			-0.03	(0.05)	
# of Metro Areas	143		143		

Notes: Means in Panel A are weighted to be representative of the manufacturing employment in the universe covered by the SMT (in SIC 34-38 and with at least twenty employees) in the plant's metropolitan area; weights calculated using the 1987 (for 1988) or 1992 (for 1993) Census of Manufactures. In Panel B, a metropolitan-level dataset was first constructed using the 1980 Census of Population and the 1987-89 (for 1988) and 1992-94 (for 1993) stacked merged outgoing rotation groups of the Current Population (CPS) surveys using CPS person weights in the latter two cases. The sample was in each case limited to those 16-65 year olds with at least one year potential experience and in the labor force at the time of the survey. In the "1988" CPSs and the 1980 Census, high school completers are defined as those who report completing twelve years of education, or who report attending but not completing thirteen years of education; in the "1993" CPSs, they are those who report highest grade completed as "High school graduate, diploma or GED." Dropouts are all workers who did not complete high school. High school equivalents are those who did plus half of those who attended four -year college but did not receive a four year degree or more. The means across these metro areas were then weighted using employment in the metropolitan area at plants eligible to be in the SMT, in other words, the same numbers used as weights in panel A. See Data Appendix for further details on the construction of these weights.

Table II. Occupation and Demographic Characteristics of SMT* Industries, 1990

Nativity:	Foreign	Native-Born			
Education:	High Schl Dropouts	High Schl Dropouts	High Schl Grads	Some College	4-yr Coll. Grads
A. Percent of Each Group's Hours in Selected Occupations (Among Workers in SMT Industries)*					
Computer and Numerical Control Machine Programmers and Operators	**0.04**	**0.02**	**0.06**	**0.11**	**0.02**
	(0.02)	**(0.01)**	**(0.01)**	**(0.01)**	**(0.01)**
Top 10 Occs of All High School Dropouts	**55.61**	**45.28**	**39.17**	**23.04**	**5.34**
Assemblers	15.25	13.46	10.39	4.81	0.71
Machinists	5.39	5.40	6.38	4.14	0.33
Production Supervisors	4.63	5.45	5.90	6.00	3.21
Machine Operators, Not Specified	7.60	4.21	2.92	1.33	0.19
Welders and cutters	4.79	5.08	3.76	1.73	0.16
Electronic equipment assemblers	7.07	3.69	2.95	1.19	0.14
Miscellaneous Machine Operators	5.47	2.65	1.98	0.89	0.10
Production inspectors	2.78	3.04	3.25	2.35	0.41
Laborers	2.61	2.28	1.63	0.61	0.09
Top 10 Occs of Native-Born College Grads	**2.29**	**3.56**	**7.04**	**20.75**	**60.36**
Managers and Administrators	1.64	2.32	3.74	8.88	19.16
Electrical Engineers	0.07	0.07	0.33	1.69	8.42
Aerospace engineers	0.00	0.05	0.21	1.14	6.75
Sales Representatives	0.42	0.72	1.33	2.74	5.21
Computer Systems Analysts	0.02	0.04	0.18	1.05	4.46
Accountants and auditors	0.00	0.06	0.32	1.10	4.35
Mechanical engineers	0.02	0.07	0.29	1.46	4.28
Managers, Marketing, Advertising and PR	0.04	0.11	0.30	1.24	4.01
Computer programmers	0.07	0.11	0.34	1.44	3.72
B. Percent of Group's Total Work Hours in SMT Industries*					
Percent of Total	8.89	9.88	9.54	8.64	6.95
Percent of Manufacturing	32.45	40.40	45.24	52.61	51.32

Data Source: 1990 Census of Population. Panel A shows, for those workers in industries covered by the *SMT (= surveys of manufacutring technology, 1990 Census industry codes 281-392, corresponding to SIC 34-38), residing in one of the 143 metropolitan areas use in the analysis, and in the education x nativity group listed in the column header, the share of hours worked in each of the occupations listed in the table's rows. Selected standard errors in parentheses. Panel B shows, for all workers , or all workers in manufacturing residing in one of the 143 metropolitan areas used in the analysis in the education x nativity group listed in the column header, the share of hours worked in industries covered by the SMT. All figures computed using 1990 census "person weights." Workers are defined to be individuals age 16-65 with at least one year of potential work experience and employed.

Table III. SMT* Technology Use and Metropolitan Skill Group Shares

	Panel A. Number of Technologies in Use					Panel B. Technologies Added
	1988	1993	Pooled			1988-93
	(1)	(2)	(3)	(4)		(5)
Share High	12.77	14.47	13.64	2.23	ΔShare High	7.08
School Grad	(4.03)	(2.48)	(2.84)	(5.93)	School Grad	(4.49)
Share Some	11.43	13.88	12.88	10.06	ΔShare Some	9.96
College	(6.08)	(4.42)	(3.97)	(5.88)	College	(5.22)
Share >=4-Year	3.34	6.53	5.00	0.76	ΔShare >=4-Year	3.66
College Grad	(3.20)	(2.45)	(2.38)	(6.10)	College Grad	(4.95)
R-squared	0.27	0.25	0.24	0.31		0.12
Industry Effects?	Y	Y	Y	Y	Industry Effects?	Y
MSA Effects?	N	N	N	Y		
Observations	6,571	4,757	11,328	11,328		4,757

Notes: Standard errors, in paretheses, are calculated to be robust to arbitrary error correlations within metropolitan area. The dependent variable is the number advanced manufacturing technologies (see Appendix Table A.1 for a list) employed (Panel A) or added over the past five years (Panel B) computed using the 1988 and 1993 *SMTs (=surveys of Manufacturing Technology). The independent variables the share of the metro area's labor force that are high school graduates, some college but no degree, and with at least a four year degree in the plant's metropolitan area (in Panel B in changes), calculated with the 1987-89 (for 1988) and 1992-94 (for 1993) merged outgoing rotation groups of the Current Population Survey, using CPS "person weights." Regressions are weighted to be representative of the area's manufacturing employment in the universe covered by the SMT (in SIC 34-38 and with at least twenty employees), which was calculated using the 1987 (for weights used in association with the 1988 SMT) or 1992 (for the 1993 SMT) Census of Manufactures. See Data Appendix for further details on the construction of these weights.

<u>Table IV</u>. First Stage Regressions

	First Stage: Change in Dropouts/High School Equivalent				Specification Check: 1980 Dropout Share	
Instrument For Years:	**1980-1988**		**1988-1993**		**1980-88**	**1988-93**
	(1)	(2)	(3)	(4)	(5)	(6)
Predicted ΔDropouts/HS	1.70	1.63	0.88	0.87	0.03	0.04
Equivalent	(0.20)	(0.19)	(0.21)	(0.20)	(0.16)	(0.23)
Dropouts/H.S. Equiv, 1980	-0.46	-0.49		-0.15		
	(0.05)	(0.07)		(0.05)		
Foreign-Born HS Dropout		0.01		0.02		
ln(e/pop), 1980		(0.03)		(0.04)		
Foreign-Born HS Dropout		-0.07		-0.07		
ln(hourly wage), 1980		(0.05)		(0.04)		
R-squared	0.69	0.70	0.20	0.29	0.00	0.00
Observations	143	143	143	143	143	143

<u>Notes</u>: Heteroskedasticity-robust standard errors in parentheses. Table shows regressions across metropolitan areas of the change in high school dropouts/high school equivalent on the change in dropouts per high school equivalent predicted by apportioning recent immigrant arrivals across metro areas according to their 1970 settlement patterns in the U.S. separately by sixteen country groups (see Data Appendix), and controls. The number of "high school equivalents" is defined to be the number who report having completed exactly twelve years of school (or obtained a GED) plus one half of those who attended college but did not receive a four-year degree. 1980 values were constructed using the five percent public-use files of the 1980 census of population; other figures were constructed using the merged outgoing rotation group files from the Current Population Survey (CPS) , using CPS "person weights," with the 1987-89 data used for 1988, and the 1992-1994 data used for 1993. Regressions are weighted by an area's manufacturing employment in the universe covered by the Surveys of Manufacturing Technology (in SIC 34-38 and with at least twenty employees), which was calculated using the 1987 (for 1980-88) or 1992 (for 1988-93) Census of Manufactures. Employment/population ("e/pop") ratios were constructed using the sample of foreign-born high school dropouts aged 16-65 with one year of poential work experience; wages were constructed using foreign-born high school dropouts aged 16-65 with one year of potential work experience, employed and with an hourly wage between $2 and $200 in 1999 dollars.

Table V. Number of Technologies Added or Planned, 1988-1993

	OLS (1)	IV (2)	OLS (3)	IV (4)
A. Number of Technlogies Added, 1988-1993				
ΔDropouts/H.S. Equiv, 1988-93	-2.32	-7.75	-3.02	-11.44
	(1.68)	(4.20)	(1.67)	(4.42)
R-squared	0.00	--	0.11	--
B. Planned Additions, 1988-93 (as of 1988)				
ΔDropouts/H.S. Equiv, 1988-93	1.19	2.43	1.71	4.79
	(1.06)	(1.65)	(1.03)	(2.40)
R-squared	0.00	--	0.07	--
Industry Effects?	N	N	Y	Y

Notes: Standard errors, in paretheses, are are calculated to be robust to arbitrary error correlation within metropolitan area. In Panel A the dependent variable is the number of advanced manufacturing technologies (see Appendix Table A1 for a list) a plant added over the past five years, from the 1993 SMT (= Survey of Manufacturing Technology) (4,757 observations total). In Panel B the dependent variable is the number of technologies a plant planned to add over the next five years, asked in the 1988 SMT (6,571 observations total). Both are regressed on the change in dropouts per high school equivalent between 1988 and 1993 in the plant's metropolitan area, calculated with the 1987-89 (for 1988) and 1992-94 (for 1993) merged outgoing rotation groups of the Current Population Survey (CPS), using CPS "person weights." The number of "high school equivalents" is defined to be the number who report having completed exactly twelve years of school (or obtained a GED) plus one half of those who attended college but did not receive a four-year degree. The instrumental variable used in regressions in columns (2) and (4) is the change in dropouts per high school equivalent predicted from apportioning national immigrant arrivals in sixteen regions of origin according to their 1970 settlement patterns (see Data Appendix and Appendix Table A.2. for details); first stage regressions are shown in Table IV. Regressions are weighted to be representative of the area's manufacturing employment in the universe covered by the SMT (in SIC 34-38 and with at least twenty employees). Weights were calculated using the 1987 (for Panel B, which uses the 1988 SMT) or 1992 (for Panel A, which uses the 1993 SMT) Census of Manufactures.

Table VI. Number of Technologies in Use in 1988

	OLS	IV	OLS	IV	OLS	IV	OLS	IV
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
ΔDropouts/HS Equivalent	-4.91	-7.02	-6.80	-9.59	-5.62	-8.21	-3.94	-4.61
1980-88	(1.61)	(2.10)	(1.79)	(2.10)	(2.02)	(1.90)	(0.97)	(1.10)
Dropouts/HS Equivalent,	-4.56	-5.30	-2.68	-3.62	-3.32	-4.17	-1.48	-1.71
1980	(1.21)	(1.40)	(1.16)	(1.24)	(1.35)	(1.23)	(0.71)	(0.75)
R-squared	0.01	--	0.27	--	0.48	--	0.55	--
Observations	6,571	6,571	6,571	6,571	6,571	6,571	6,571	6,571
Industry?	N	N	Y	Y	Y	Y	Y	Y
Industry x Price?	N	N	N	N	Y	Y	N	N
Log Employment	N	N	N	N	N	N	Y	Y

Notes: Standard errors, in paretheses, are calculated to be robust to arbitrary error correlation within metropolitan area. The table shows regressions where the dependent variable is the number of advanced manufacturing technologies in use (see Appendix Table A1 for a list) at a plant in the 1988 or Survey of Manufacturing Technology (SMT). Independent variables are the change in dropouts per high school equivalent since 1980 and dropouts per high school equivalent in 1980 in the plant's metropolitan area, calculated with the 1987-89 (for 1988) merged outgoing rotation groups of the Current Population Survey (CPS), using CPS "person weights," and the 1980 five percent public-use census of population data (for 1980). The number of "high school equivalents" is defined to be the number who report having completed exactly twelve years of school (or obtained a GED) plus one half of those who attended college but did not receive a four-year degree. The instrumental variable used in regressions in columns (2) , (4), (6), and (8) is the change in dropouts per high school equivalent predicted from apportioning national immigrant arrivals in sixteen regions of origin according to their 1970 settlement patterns (see Data Appendix and Appendix Table A.2. for details); first stage regressions are shown in Table IV. Regressions are weighted to be representative of manufacturing employment in the universe covered by the SMT (in SIC 34-38 and with at least 20 employees) in the plant's metropolitan area, which was calculated using the 1987 Census of Manufactures.

<u>Table VII</u>. Changes in Machinery Per Worker and Value Added Per Worker, 1987-1992

	OLS	IV
	(1)	(2)
A. ln(Machinery/Worker)		
ΔDropouts/H.S.	-0.16	-0.59
Equivalent	(0.16)	(0.31)
R-squared	0.01	--
B. ln(Value Added/Worker)		
ΔDropouts/H.S.	-0.14	-0.03
Equivalent	(0.10)	(0.24)
R-squared	0.01	--
Industry Effects?	Y	Y
Plant-Year Obs:	163,902	163,902

<u>Notes</u>: Data source of dependent variables: 1987 and 1992 Census of Manufactures. Standard errors in parentheses. In Panel A, the dependent variable is the adjusted change in average of the natural log of the book value of machinery per worker. In Panel B, the dependent variables is the adjusted change in average of the natural log of value added per worker. The independent variable is dropouts per high school equivalent in the plant's metropolitan area, calculated with the 1987-89 (for 1987) and 1992-94 (for 1992) merged outgoing rotation groups of the Current Population Survey, using CPS "person weights."The number of "high school equivalents" is defined to be the number who report having completed exactly twelve years of school (or obtained a GED) plus one half of those who attended college but did not receive a four-year degree. Regressions were performed in two stages. First, the dependent variable regressed on metro area effects and (four-digit) industry effects separately for each year (1987, 1992). The estimated metro effects are the adjusted changes used as the dependent variable. The instrumental variable used in regressions in column (2) is the change in dropouts per high school equivalent predicted from apportioning national immigrant arrivals in sixteen regions of origin according to their 1970 settlement patterns (see Data Appendix and Appendix Table A.2. for details); first stage regressions are shown in Table IV.

Table VIII. Manufacturing Wages

Wage Outcome:	Dropout-High School Wage Gap				Coll-HS Gap
Data Source:	CPS	Census			Census
Sample:	All*	All*	Native Born	Native Born	Native Born
	(1)	(2)	(3)	(4)	(5)
	A. Instrumental Variables				
Δ Dropouts/	-0.136	-0.199	-0.143	-0.277	0.474
HS Equivalent	(0.282)	(0.0406)	(0.0426)	(0.176)	(0.273)
Δ College Equivalents/				0.323	-0.613
HS Equivalent				(0.370)	(0.397)
	B. Ordinary Least Squares				
Δ Dropouts/	0.0916	-0.128	0.0370	0.0582	0.0544
HS Equivalent	(0.198)	(0.0225)	(0.0313)	(0.0353)	(0.0336)
Δ College Equivalents/				-0.0453	0.0395
HS Equivalent				(0.0440)	(0.0518)
Individual Controls*	Yes	Yes	Yes	Yes	Yes
Year Effects?	Yes	Yes	Yes	Yes	Yes

Data sources: 1987, 1988, 1989, 1992, 1993, and 1994 merged outgoing rotation groups of the Current Population Survey ("CPS"); 1980, 1990, and 2000 five percent public-use censuses of population ("Census"). Observations on the same 143 metropolitan areas examined in previous tables. Wage outcomes: Columns (1)-(4) : Change in the regression adjusted wage gap between high school dropouts and high school completers. *Among 20-65 year olds with between nine and twelve years of education, at least one year of potential experience (age-years of education - 6) and with an hourly wage between $2 and $200 in 1999 dollars, the log hourly wage gap between dropouts and graduates was adjusted for a quadratic in years of education, a quartic in potential work experience, a dummy for being born after 1950 and its interaction with years of education, and dummies for black, female and their interaction. Column (1) stacks 1987-1989 CPSs into "1988" data and 1992-1994 CPSs into "1993" data, and in addition to the above, also controls for survey year effects in the wage adjustment. In the "1988" CPSs and the 1980 Census, high school completers are those who report completing twelve years of education, or who report attending but not completing thirteen years of education; in the 1990 Census and "1993" CPSs, they are those who report highest grade completed as "High school graduate, diploma or GED."; in the 2000 Census they are those who report being a "High school graduate." Dropouts are those who report less education (but at least completed 9 years of education). Column (5): Change in the regression-adjusted wage gap between four-year college graduates and high school graduates. Among 20-65 year olds with exactly twelve or sixteen years of education, at least one year of potential experience and with an hourly wage between $2 and $200 in 1999 dollars, the log hourly wage gap between college and high school workers was adjusted the same as above, but without the quadratic in years of education. Estimates in columns (3)-(5) exclude noncitizens and naturalized citizens from the wage sample.

Table shows slope estimates from regressions of the change in these wage outcomes on the change in dropouts per high school equivalent (number of high school dropouts + 1/2 number of those with some college education, but no four-year degree) and the change in college equivalents (number of four-year college graduates plus 1/2 of those with some college education) per high school equivalent. Standrard errors, in parenthesis, are constructed to be consistent under arbitrary error correlation over time in each metropolitan area. Regressions in column (1) are weighted by the metro area's 1990 manufacturing employment (estimated using the 1990 census); and regressions in columns (2)-(5) are weighted by end of decade metropolitan area manufacturing employment (estimated with the 1990 and 2000 census). The instrumental is the changes in dropouts per high school equivalent and college equivalents per high school equivalent predicted by apportioning national immigrant arrivals from sixteen regions of origin (Appendix Table A.2.) according to their settlement patterns in 1970 (in columns (1)) or the decade prior to the beginning of decade (1970 for 1980-90, 1980 for 1990-2000 in columns (2)-(5)) . The first stage coefficient (standard error) for column (1) is .866(.182) , for columns (2)-(3) is .808 (.181). In column (4) the first stage coefficient (standard error) on the dropout instrument is 1.08(0.267) and on the college instrument is 2.76 (1.14) with an overall instrument F-stat of 8.76. In column (5) the first stage coefficient on the dropout instrument is 0.59 2(0.168) and on the college instrument is 2.6 2(0.558) with an overall instrument F-stat of 14.82.

Figure I. Two-Sector Model