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Abstract

A series of studies has found that relative wages and employment rates in different local labor markets of the US are surprisingly unaffected by local factor supplies. This paper evaluates two explanations for this puzzling empirical fact: (1) Interregional trade mitigates the local impact of supply shocks. (2) Production technology rapidly adapts to the local mix of workers. I test these alternative explanations by estimating the effect of increases in relative supplies of particular skill groups on the relative growth rates of different industries and on the relative utilization of these skill groups within industries. Labor supply shocks are identified with a component of foreign immigration driven by the historical regional settlement patterns of immigrants from different countries. Using establishment-level output and capital stock data from the Longitudinal Research Database, augmented with employment and labor force data from the 1980 and 1990 Censuses of Population, changes in local labor supply during the 1980s are shown to have had little influence on local industry mix. Instead, citywide increases in the relative supply of a particular skill group lead to increases in relative factor intensity, with little or no effect on relative wages. These patterns suggest that industries adapt their use of labor inputs to local supplies, as predicted by theoretical models of endogenous technological change. Consistent with this interpretation, on-the-job computer use expanded most rapidly over the 1980s in cities where the relative supply of educated labor grew fastest.

JEL J2, F1, O3.
Keywords: Immigration, Heckscher-Ohlin, Endogenous Technological Change

1. Introduction and Background

How do local labor markets respond to changes in the relative supplies of different types of labor? The simple closed-economy supply-demand framework fits the data poorly: wages and employment rates are consistently unresponsive to local labor supply mix in comparisons across regions of the US. Moreover, a number of careful empirical studies have found that large-scale inflows of immigrants have little impact on wages or employment rates of competing natives. (Surveys include Borjas (1994) and Friedberg and Hunt (1995).) For example, the relative wages of less-educated workers evolved similarly in California labor markets and in other parts of the US during the 1980s at the same time as California's markets took on a massive net increase in the relative supply of less-educated labor, due largely to immigration.[1]

Motivated by this empirical puzzle, this paper evaluates the importance of mechanisms other than changes in factor prices or employment rates for responding to changes in the local supply of labor. I focus on two explanations: (1) US cities are not closed economies, but are better described as Heckscher-Ohlin (hereafter, "HO") open economies, which can trade away local skill imbalances by specializing in production; and (2) production technology adapts to the local skill mix of workers.

In the HO model, local imbalances in labor supply are accommodated by exporting goods intensive in the relevant labor type. In the most extreme version, local industry structure adjusts enough so that local labor supply has no impact on relative wages or employment

[1] This will be demonstrated below.

rates. Although this possibility has been noted by several authors (including Borjas, Freeman and Katz (1996)), it remains largely untested in the context of US labor markets. HO theory has not been particularly successful in describing differences across countries.[2] At the international level, however, deviations from HO assumptions (no trade barriers, identical technologies) are substantial. Different US cities are more likely to satisfy these assumptions. In this regard, the present paper follows recent work that evaluates HO within countries (Davis et. al (1997) in Japan; Hanson and Slaughter (2002) and Quispe-Agnoli and Zavodny (2002) in the US; and Bernard, Redding et. al (2002) in the UK).[3]

The second alternative is that worker productivity differs across localities. A paper by Trefler (1993), motivated by the empirical failure of HO, shows that allowing countries to have factor-specific productivity differences common to all industries generates a consistent fit to the cross-country trade and factor price data.[4] For this theory to explain the limited responsiveness of wages and employment rates to local labor supply in the US, local productivity differences must be driven by a phenomenon that raises the relative productivities of a given labor type with an increase in its relative supply. A phenomenon fitting this description appears in a recent model by Acemoglu (2002): technology is endogenously chosen to complement the work force.[5] Acemoglu's research repeats a

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2 Davis et al. (1997) called it a "flop."

3 Besides intercity goods trade, it is possible that skill imbalances generated by immigration could be accommodated by intercity *labor* flows. However, as shown below, in many less-skilled immigrant cities, like LA and Miami, the relative supply of less-skilled workers grew tremendously compared to other cities. In any case, this issue can also be addressed by focusing on the overall skill mix of the local labor force, rather than just the part due to foreign immigration. This is the approach taken here.

4 Hanson and Slaughter's (2002) interpret changes across US states during the 1980s as support Trefler's version of HO.

5 Another explanation is that observed labor flows are in part an endogenous response to local demand (Borjas (1994) and Borjas, Freeman and Katz (1996)). This problem is addressed in the literature by using instruments for immigrant inflows based on historical settlement patterns, with the general finding that the estimated

common explanation for the puzzling recent coincidence of rising supply and relative wages of college graduates – it was driven by the spread of "skill-biased" technologies, which replace unskilled and complement skilled workers – but innovatively conjectures that skill-biased technological change may have been in part an *endogenous* response to the growing availability of more educated workers. In this view, computer technology became more cost effective and thus became widespread as the work force became more educated.[6] In comparisons across labor markets, therefore, skill-biased technologies may be most prevalent where the relative supply of skilled labor is rising most rapidly.

In this paper, I analyze changes in local supplies of four skill groups (defined by education) across major metropolitan areas. I decompose relative supply changes in each of the cities over the 1980s into an expansion of the industries that tend to employ a given type of labor, and changes in the intensity of its use within industries. The former supports an HO description of the world, while the latter – absent relative wage changes – is consistent with the idea that factor-biased technical change accommodates the changes in skill mix. To further examine the latter explanation, I also examine how changes in local labor supply affect on-the-job computer use.

I examine the question in two contexts. I start by examining industrial changes in several California cities and Miami where, atypical of the rest of the country, the availability of high

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impacts remain small. Moreover, studies of massive refugee flows (such as the Mariel boatlift) would seem to be immune from the endogeneity problem, and yet show similarly small effects of local labor supply on wages.

[6]Acemoglu also quotes Habakkuk's (1962) observation that in the 19th century, skill-replacing factory-style production may have been introduced because unskilled labor became plentiful in cities. In the present cross-city context, Acemoglu's (2002) model might say that where low-skill immigration reduced the relative supply of skilled labor, computers were less cost-effective and therefore introduced more slowly, reducing downward pressure on low-skill wages.

school dropouts grew during the 1980s (due largely to immigration). To control for unobserved determinants of labor mix in these cities, I compare them with another group of labor markets matched on their industrial mix at the beginning of the decade. Second, I use a regression framework to evaluate how changes in labor mix in 179 US metropolitan areas during the 1980s impacted their mix of industries, or, alternatively, their skill mix within industries. An instrumental variables strategy is used to identify exogenous changes in worker mix in this part of the analysis, where the instrument derives from the settlement patterns of immigrants across metropolitan labor markets in 1970.

For the purposes of evaluating HO, special attention is given to the response of industries in the manufacturing sector, as it is a major traded goods sector and because detailed data are available: I will use firm-level output and capital stock data from the confidential micro data version of the Annual Surveys of Manufactures available in the Census Bureau's Longitudinal Research Database. I supplement this with data on other sectors, using employment data from the 1980 and 1990 Census of Population (which I show performs similarly to output and capital data for manufacturing). The population censuses are also used to measure the growth in labor availability in US metropolitan areas.

I find in each case that while changes in labor supply have some influence on the mix of industries (for example, apparel tends to grow with the supply of less-educated labor), these responses are typically small in comparison to the supply changes. I find that industries that employ dropouts in California cities and in Miami did not grow, on average, any faster than in matched comparison cities, even though the former group took on unusually large numbers of less-educated workers during the 1980s. Across the 179 metropolitan areas, cities that received more of one type of labor had little greater tendency than other cities to "grow" industries that tend to employ it.

In contrast to the relatively unresponsive patterns of industry growth, the skill intensity of most industries is highly responsive to city-specific changes in skill mix. An increase in the relative supply of some type of labor leads to an increased intensity of its use across a wide range of industries that is, on average, around 80 percent as large as the supply change. Unexpected sectors like finance and professional services took on a relatively greater share of dropout labor where it was locally abundant.[7] In a standard model this increase in relative use within industry would imply relative wage changes, but similar to previous research, I find that wages are relatively unresponsive to local supply, lending support to the idea that there were accommodating changes in production technology. Consistent with this, computer use at work grew more rapidly in cities where the work force became relatively more educated.

2. Empirical Framework

This section presents a framework for evaluating the impact of labor supply shocks on a local labor market. Start with the identity that the supply of workers of type *i* is the sum of the employment of these workers in each sector *j*, plus any unemployment $L_i = N_i + U_i = \sum_j N_{ij} + U_i$. This paper analyzes the response of

[7] Similar results occur within narrow occupations – the education of workers hired for particular occupations appears to depend heavily on the education mix of the local work force (Lewis (2003)).

employment to the *growth* of different labor inputs, so taking the first difference of both sides of and dividing through by L_i produces the employment growth identity:

$$(1)\ \frac{\Delta L_i}{L_i} = \%\Delta L_i = \sum_j s_{ij0}\%\Delta N_{ij} + s_{iU0}\%\Delta U_i$$

where $s_{ij0} = N_{ij0}/L_{i0}$ and $s_{iU0} = U_{i0}/L_{i0}$ are the initial shares of type-*i* workers employed in sector *j* and unemployed. Next, employment growth is further decomposed into industry mix changes and changes in type-*i* labor intensity. So let M_j be a measure of the size or scale of sector *j* such as output or total employment. This relates to type-*i* employment in the sector by the identity $N_{ij} = M_j\left(\frac{N_{ij}}{M_j}\right)$.[8] In growth terms, this is:

$$\%\Delta N_{ij} = \%\Delta M_j + \%\Delta\left(\frac{N_{ij}}{M_j}\right) + \%\Delta M_j \cdot \%\Delta\left(\frac{N_{ij}}{M_j}\right)$$

So the growth in type-*i* employment in sector-*j* can be decomposed into the growth in scale of the sector, $\%\Delta M_j$, holding constant factor intensity, and the growth in the number of type-*i* workers per unit scale, $\%\Delta\left(\frac{N_{ij}}{M_j}\right)$ (i.e. growth in the type-*i* labor intensity of the sector) holding constant industry scale. Where each component is held constant matters for

[8] Note that summed across sectors this is the usual HO accounting identity. Different measures of scale are equivalent with this type of measure under the assumption of constant returns to scale.

the decomposition; a third term, not uniquely assignable to either of the first two components, gives the full range of possible decompositions.[9]

Substituting this expression into (1) produces a general decomposition of the growth in type-*i* labor force:

$$(2)\ \%\Delta L_i = \sum_j s_{ij0}\%\Delta M_j + \sum_j s_{ij0}\%\Delta\left(\frac{N_{ij}}{M_j}\right) + \sum_j s_{ij0}\%\Delta M_j \cdot \%\Delta\left(\frac{N_{ij}}{M_j}\right) + s_{iU0}\%\Delta U_i$$

There are four terms in this decomposition:

(1) Growth in the scale of the average type-*i* employing industry, at fixed factor ratios;

(2) Growth in the average type-*i* employing industry's type-*i* intensity, for a fixed mix of industries;

(3) A term consisting of (1) and (2) (it cannot be uniquely assigned to either);[10] and

(4) Growth in unemployment

The first term measures changes in labor mix absorbed "between" industries, and the second term "within" industries. HO is a full employment model, in which (absent exogenous technical change, considered below) factor prices are determined externally, so each sector's factor intensities are unaffected by labor supply. Thus, according to HO:

[9] This type of decomposition customarily is evaluated at the mean of the two periods, which implicitly assigns half of this third term to each of the first two components. This makes it appear in other work that there is a unique decomposition into "within" industry and "between" industry components. (Examples include Hanson and Slaughter (2002) and Autor, Katz and Krueger (1998).) I instead take the approach of writing down this general identity, and then showing that in practice the third "ambiguous" term is small; thus any kind of decomposition would give roughly the same answer.

[10] In practice, this third term also includes industries whose base year scale is so small (or 0) that it is impossible to get a reliable estimate of its growth.

$$(3)\ \%\Delta L_i = \sum_j s_{ij0} \%\Delta M_j$$

One way to describe the prediction of HO, then, is that in the long run, the industries that tend to employ some factor grow, on average, as much as the supply of that factor.[11] If this is not true, then there are by definition changes in skill intensity within industry or higher rates of unemployment.

Empirical Implementation

Several issues complicate empirical assessment of (2). First among these is that the skill intensity of sectors may change over time for exogenous reasons (i.e. technical change), implying the second and third terms of equation (2) may not actually be 0 even in a world where HO held perfectly. To validly evaluate the HO model, it is necessary to control for counterfactual changes in skill intensity. One approach I will take is to compare regions that are initially similar in industry structure but which faced different relative labor supply changes. In the regressions of section 5 the influence of changes in production technology is modeled as a skill-group fixed effect common to all cities plus idiosyncratic local noise assumed to be orthogonal to the labor shocks. In both cases the key assumption is that technology shocks are similar across cities.

[11] This is the "Rybczynski theorem" (see Leamer (1995) for a good description) written in growth terms.

A second empirical issue is that not all goods are traded – some are local.[12] Ethier (1972) shows that in this case industry mix changes take place entirely through the traded sector, so the right-hand side of (3) is modified to include only traded sectors.[13] In this paper I give special attention to the adjustments in the manufacturing sector.

Another problem is that growth in the scale of the economy can generate an apparent relationship between factor supplies and industry growth by raising both simultaneously. Such a relationship would occur even in an economy closed to goods trade. This can be addressed by controlling for changes in the scale of the economy.

The biggest problem is that while we are interested in estimating how labor supply shocks are absorbed, differences in labor demand across localities may confound the relationship. For example, a local increase in consumer demand for some good would lead to an expansion of that sector and might also draw suitable workers into the market, simultaneously raising both sides of equation (3) and making it appear that increased quantities of labor generated industry growth, when in fact the causality was the other way. In addition, local factor-specific or industry-factor-specific productivity shocks could draw workers into a locality; these types of demand shocks would raise the second and third terms

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[12] In fact, this potentially affects the HO result itself: as modeled in Ethier (1972) and Komiya (1967), the arrival of new workers affects demand for local goods, which affects the inputs available to traded industries. In extreme cases, this can lead to a failure of the theorem; however, Ethier (1972) showed that if the ratio of marginal to average propensity to consume for the non-traded good does not exceed the inverse of capital's share of income, HO continues to hold. Homothetic preferences are sufficient for this.

[13] Technically one should also adjust changes in labor supply to account for what is absorbed into the non-traded sector. However, using the *actual* change in non-traded employment is problematic because it may be endogenous to the overall supply change in a more general framework than HO. One approach would be to use the theoretical change in non-traded employment under HO consistent assumptions, e.g. homotheticity. It is worth noting that at least for the specifications I have tried, adjusting labor supply changes for either actual or theoretical employment changes in the non-traded sector does not substantially alter the empirical results of this paper.

of (2). Both concerns will be addressed by attempting to identify exogenous sources of variation in labor mix changes across markets.

3. Data

This paper uses three primary sources of data: labor force and employment data from the 1990 and 1980 Census of Population 5 percent microsample (PUMS) and manufacturing data from the Annual Survey of Manufactures (ASM). The 1970 Census of Population 1 percent county group files are used to construct the instrument, described in section 5.

This section describes the ASM; further details on how these data were linked for this project can be found in the data appendix.

Longitudinal Research Database Survey Designs

The ASM data used in this project were made available in the Census Bureau's Longitudinal Research Database (LRD), a confidential dataset that links establishment-level survey data from Censuses of Manufactures, (CM) occurring once every five years (in years ending in "2" and "7") and the Annual Survey of Manufactures (ASM), occurring every year.[14] This project uses the ASM data. An establishment is (usually) defined as a physical location where production takes place.[15]

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[14] The description of the LRD and the ASM in this section is based upon LRD documentation (US Department of Commerce (1999)), appendices to the Census Bureau's industry series reports, (for example, US Department of Commerce (2002)) and ASM and CM survey forms, available on the Census Bureau's web site.

[15] It sometimes happens that a single large establishment produces distinct product lines; when the amounts are significant, the Census Bureau attempts to treat each product line within the same physical location as a separate establishment.

The ASM, whose survey design goal is to produce reliable aggregate statistics on shipments by industry, collects detailed shipment, cost, and asset information from a sample of manufacturing establishments each year. Beginning two years after a CM, firms are selected to be in the ASM using the previous CM as the sampling frame. Large establishments, and ones that produce a large share of any industry's output, are always included in the ASM. Very small establishments are excluded from the survey. Among medium establishments, a random sample is drawn, stratified on firm size. Once selected, an establishment is surveyed every year (unless it shuts down) for the subsequent five years. It is not quite correct to call this a panel, however. To maintain the representativeness of the sample, the ASM may add newly active firms during the five-year period, using updated records on the universe of manufacturing establishments.[16]

A weakness of the ASM is that very small firms are not observed, and since the present project is concerned with measuring aggregate growth in each industry, it would be a problem if small manufacturing firms were where much of the action was. ASM documentation reports that the data are representative of the vast majority of production; in addition, results obtained using data that do not have this weakness are quite similar.

16 Lists of enterprises come from IRS and Social Security Administration records. In addition, the Census Bureau surveys manufacturing enterprises to obtain lists of new establishments opened by multi-unit enterprises. Davis, Haltiwanger and Schuh (1991) present evidence that the Bureau is not entirely successful in maintaining the representativeness of the sample within a panel but also show that long-term employment growth, measured between panels, is unbiased.

Measuring Output and Capital in the ASM

Output or value added in the ASM is measured as the total value of shipments minus materials and energy costs (with adjustments for inventory changes). This definition avoids the double counting of intermediate goods produced in the manufacturing sector. Capital stock is measured as the end-of-year book value of equipment and structures.

4. An Examination of Dropout-Receiving Cities

During the 1980s, the proportion of workers with less than a high school education declined rapidly in most parts of the US, but in much of California and in Miami, the relative supply of dropouts stayed roughly constant or even increased. This was due mostly to the influx of Cuban migrants to Miami (especially during the Mariel boatlift) and the accelerating wave of Mexican immigration to California. This section examines how these cities adapted to their growing relative abundance of high school dropout workers. Did high school dropout employment rates or wages face relative decline? Did dropout-intensive industries experience relative growth? Were dropouts employed relatively more intensively? Or was it some of each?

Table 1 lists the major metropolitan areas with the largest relative increases in high school dropout labor force during the 1980s, which will be analyzed in this section. The first column of the table shows the growth in labor supply of high school dropouts relative to non-dropouts over the 1980s, the measure on which these cities were selected for analysis.[17] Los Angeles and Anaheim metro areas experienced the largest relative growth in dropout labor supply, 12 percent and 9 percent, respectively; Miami experienced a 4 percent growth. The region consisting of the seven "treatment" cities averaged a 7 percent relative growth in high school dropout supply. In contrast, the continental US experienced a 43 percent decline in its dropout labor force per capita relative to other types of workers.[18] The unusual growth in dropout work force in these cities is associated with foreign immigration: column 4 shows the immigrant labor force grew by 70 percent in per capita terms in the average of the dropout-receiving cities, compared to half as much in the continental US. In addition, column 5 shows that the relative availability of high school dropout workers among *natives* declined at similar rates in these cities as in the lower 48 states (by 32 percent in the dropout receiving cities; 37 percent in the continental US).

The main region that dropout-receiving cities will be compared to is not the rest of the continental US, however, but a group of "comparison" cities (listed in a footnote to the table), chosen because they initially (i.e. in 1980) employed high school dropouts in a similar mix of industries: the vector of dropout employment shares across industries was similar in the comparison cities as in the dropout-receiving cities in 1980.[19] An advantage of this

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[17] Three smaller metro areas, (Yakima, WA; Merced, CA and Visalia, CA) also would fit into this list, but they were not used in the analysis, and doing so would not alter the results. Smaller cities were also excluded from the comparison group.

[18] Because of their geographic separation, Alaska and Hawaii are excluded from all of the analysis in this paper. However, including them (for example, adding Anchorage and Honolulu metropolitan areas to the regressions in the next section) has little effect on the results.

[19] A Euclidian distance measure was used to find the comparison cities. Letting s_{ijT} be the share of dropouts in industry *j* in the dropout receiving cities in 1980, and s_{ijC} is the share of dropouts in industry *j* in the city c (not in T) in 1980, the comparison region was chosen by choosing cities with the smallest value of $\Sigma_j(s_{ijT} - s_{ijC})^2$. Philadelphia was the best match on this measure. How far down the list of "matches" one goes in constructing the comparison group is immaterial to the results that follow.

choice of comparison region is that national industry demand shocks should have a similar impact on the employment of high school dropouts in the treatment and comparison regions. In addition, the education mix of workers and the unemployment rate of high school dropouts were similar in both regions in 1980.[20] The overall relative decline in high school dropout supply in the comparison cities is also similar to the trend in the nation as a whole. In each comparison city, including the other California cities (Oakland, San Diego), the relative supply of dropouts fell over the decade.

Overall, the dropout workforce grew by 7 percent in the treatment cities and declined 44 percent in the comparison cities, a 51 percentage point difference, shown in the last row of the table. Given this and the initial similarity of their labor markets, we might expect to see some difference in the evolution of wages or employment rates of high school dropouts between the two regions. However, columns 2 and 3 of Table 1 show the wages and employment rates of dropouts relative to non-dropouts evolved similarly over the decade in each region. The relative wages of high school dropouts fell by 22 percent in the dropout-receiving cities, part of a national trend of falling wages for less-skilled workers: dropout/non-dropout relative wages also fell by 26 percent nationally and by 20 percent in the comparison cities. The difference between the two regions in the growth of the relative wages of dropouts is statistically insignificant. There is also only slight evidence of negative impact on employment: relative employment/labor force rates for high school dropouts fell by 3 percent in the dropout-receiving cities and 2 percent elsewhere, a difference that is

[20] Around 13 percent of dropouts were unemployed in 1980 in both regions.

small (but statistically significant).[21] It is particularly small relative to the 51 percentage point difference in relative supply growth of dropouts. While one can never rule out that the influx of dropouts to these California cities and to Miami was demand driven, and that in its absence relative wages and employment rates of dropouts would have grown, it seems more plausible mechanisms other than changes in wages or employment rates were involved in the adjustment of these labor markets to the influx. I now turn to the examination of two particular types of adjustments: changes in industry mix and changes in production technology.

Decomposing the Growth of Dropouts

As was introduced above in equation (2), one can decompose the growth in the supply of dropouts into the growth in the average industry's size, the growth in the average industry's dropout intensity, an ambiguous term, and the growth in unemployment. Ignoring for the moment the third and fourth terms, I will rewrite (2) as follows for the present analysis:

$$\text{(2')}\quad \left(\%\Delta L_{dropout} - \%\Delta P\right)_T - \left(\%\Delta L_{dropout} - \%\Delta P\right)_C$$

$$= \sum_j s^{1980}_{dropout,j} \left[\left(\%\Delta M_j - \%\Delta P\right)_T - \left(\%\Delta M_j - \%\Delta P\right)_C\right]$$

$$+ \sum_j s^{1980}_{dropout,j} \left[\%\Delta\left(\frac{N_{dropout,j}}{M_j}\right)_T - \%\Delta\left(\frac{N_{dropout,j}}{M_j}\right)_C\right]$$

$$+ \textit{ other terms}$$

[21] Growth in other employment measures, such as participation rates, was also similar in both regions.

$\left(\%\Delta L_{dropout} - \%\Delta P\right)_T - \left(\%\Delta L_{dropout} - \%\Delta P\right)_C$ represents the growth of dropout workers in excess of population ($\%\Delta P$ is included to absorb changes in city scale) in the dropout-receiving cities, T, relative to the comparison cities, C. This measure of the relative growth of dropout labor supply has a value of 0.56.[22] This can be decomposed into the relative growth in the size of the average dropout-employing industry (first term) plus the growth in dropout intensity within industries (second term), plus unemployment (not shown).[23] Note that this decomposition is simplified by the fact that shares of dropouts employed in each industry $s_{dropout,j}^{1980}$ are, by design, initially approximately equal in the dropout-receiving cities and the comparison cities.[24]

It is convenient to normalize (2') by dividing by $\left(\%\Delta L_{dropout} - \%\Delta P\right)_T - \left(\%\Delta L_{dropout} - \%\Delta P\right)_C$, so that each term represents the *share* of the relative growth in dropouts absorbed within or between industries. For example, the first term in the decomposition becomes:

$$(3')\quad \sum_j s_{dropout,j,T}^{1980}\left[\frac{\left(\%\Delta M_j - \%\Delta P\right)_T - \left(\%\Delta M_j - \%\Delta P\right)_C}{\left(\%\Delta L_{dropout} - \%\Delta P\right)_T - \left(\%\Delta L_{dropout} - \%\Delta P\right)_C}\right]$$

[22]I will refer to this as the "growth in the relative supply of dropouts" though to be strictly speaking true, the growth in population term should be replaced by the growth of non-dropout labor. The distinction would be of concern here if the growth in labor force per population by non-dropouts differed substantially between the treatment and comparison cities, but this is not the case. In particular, Table 1 shows the difference in the growth in the supply of dropouts relative to other workers was 0.51, which not that different from 0.56.

[23]The third non-strict part of the decomposition will turn out to be empirically unimportant in this case.

[24] And the fact that the unemployment rate of dropouts was initially approximately equal in the two regions. The shares for the dropout-receiving cities are used in the analysis.

The term in brackets measures the growth of industry j in the dropout-receiving cities relative to the comparison cities, indexed by the relative growth in the supply of high school dropout labor. A value of one means that an industry grew by enough to maintain its share of dropout employment without altering labor-use ratios. The average of this index over all industries (weighted by the initial employment share of dropouts, $s^{1980}_{dropout,j,T}$) measures the share of new dropouts absorbed by changes in industry mix, i.e. the "between" industry share. For the open economy model to be empirically successful, this share should be large.

I begin by displaying this industry growth index separately for each industry. Figure 1 plots normalized output (Q) growth ($\frac{(\hat{Q}_j-\hat{P})_T-(\hat{Q}_j-\hat{P})_C}{(\hat{L}_{dropout}-\hat{P})_T-(\hat{L}_{dropout}-\hat{P})_C}$) against initial employment share $s^{1980}_{dropout,j,T}$ for each 3-digit manufacturing industry.[25] For readability, the x-axis has been scaled logarithmically. The figure includes industries that are declining and industries that are growing, some by more than twice as much as the relative supply of dropouts. The manufacturing industry that is the biggest employer of dropouts – apparel – grew as fast as the supply of dropouts, which lends some support to HO. A similar stylized fact was noticed by Leamer and Levinsohn (1995) about one of the cities being examined – Los Angeles – and was taken by them as evidence in favor of HO. But it is evident in Figure 1 that the *typical* manufacturing industry did not experience relative growth.

What about industries outside manufacturing? The manufacturing sector in aggregate is less than a third of dropout employment; so Figure 1 might be missing growing industries.

[25] A few industries were so small in this region that publishing their data would violate confidentiality rules. For these sectors, the data point is suppressed. These sectors, however, are included in the weighted averages in Table 1.2.

Recall, however, that in order to support the open economy model, the growing sectors must produce goods or services that are exportable. Many of the other big industries that employ dropouts in Miami and California, such as household services and construction, cannot be convincingly called "traded goods." Nevertheless, I will look for evidence of dropout-absorbing changes in industry mix using all industries.

Because equivalent measures of output are not available for non-manufacturing sectors, here I switch to using PUMS data on total employment as the measure of industry size. In other words, I substitute for the output growth index the following employment growth index:

$$\frac{\left(\%\Delta N_j - \%\Delta P\right)_T - \left(\%\Delta N_j - \%\Delta P\right)_C}{\left(\%\Delta L_{dropout} - \%\Delta P\right)_T - \left(\%\Delta L_{dropout} - \%\Delta P\right)_C}$$

where $\%\Delta N_j$ represents total employment growth of industry *j*. Among manufacturing industries this index grows similarly to the output growth index: an OLS regression across industries of the output growth index on the employment growth index does not reject that a slope 1, intercept 0 line goes through the points. In addition, the largest sectors appear to have very similar changes in both datasets.

Figure 2 plots the employment growth index against the 1980 dropout employment share for each industry. The growth in household workers and agriculture is particularly striking in this figure, but once again, the points are centered around zero. The two biggest employers of dropouts, construction and restaurants, shown no pattern of relative expansion in the high dropout growth cities.

The impact of the changes shown in Figures 1 and 2 is summarized in the first column of Table 2, which shows the dropout share-weighted average of the industry growth indexes (see (3')). Recall that this measures the share of the growth in the supply of dropouts absorbed by changes in industry mix. The -0.04 in the first row, for example, says that -4 percent of the relative growth in dropouts was absorbed by changes in relative sizes of manufacturing industries, as measured by output. Measuring industry growth with employment produces a statistically insignificant estimate of 1 percent among manufacturing industries and –12 percent using all industries. In summary, it does not appear that the influx of less-skilled workers to certain California metropolitan areas and to Miami during the 1980s was associated with a change in the mix of industries that might have accommodated these new workers.

Dropout Intensity

Since it doesn't appear that dropout-intensive sectors were growing relatively faster in the high dropout growth cities, some sectors in these cities must have become relatively more intensive in their use of dropouts. To confirm this, the second column of Table 2 measures the impact of increases in dropout intensity on the relative employment of dropouts, i.e. the second term of the decomposition:

$$\sum_j s_{dropout,j,T}^{1980}\left[\frac{\%\Delta\left(\frac{N_{dropout,j}}{M_j}\right)_T-\%\Delta\left(\frac{N_{dropout,j}}{M_j}\right)_C}{\left(\%\Delta L_{dropout}-\%\Delta P\right)_T-\left(\%\Delta L_{dropout}-\%\Delta P\right)_C}\right]$$

($M_j \equiv Q_j, N_j$ as labeled.) Table 2 shows that increases in dropouts per dollar of manufacturing output accounts for 37 percent of the growth in the supply of these workers, more than manufacturing's 30 percent initial share of dropout employment. Looking at the employment data, the average industry became more dropout-intensive by a factor 0.83 as large as supply. Put another way, this says that 83 percent of the rise in the supply of dropouts went into an increase in the dropout-intensity of the average industry, or 83 percent was absorbed "within" industry.

It is also striking how widely spread across industries these changes were. To see this, Figure 3 plots the normalized relative growth in the fraction of employment that is dropouts for all industries – the term in brackets above – against the initial employment shares, $s_{dropout,j,T}^{1980}$. It shows that even unlikely sectors such as finance and real estate seem to have taken on more dropout workers. A majority of the points cannot be statistically distinguished from the mean of 0.83; if anything, the smallest dropout-employing sectors took on dropouts at a faster rate.[26] (This is shown as the downward sloping line estimated through the points.) Not surprisingly, construction was able to take on more than its share of dropouts, but

[26] Note that this could also be due to "regression to the mean" – industries whose employment of high school dropouts was underestimated in 1980 would experience, on average, apparently larger within-industry growth of high school dropouts during the decade. A similar result is obtained when national base year shares are used in place of local ones, suggesting that regression to the mean is probably only part of the source for this result.

industries that one might expect would be able to flexibly make use of additional dropouts, like retail apparel and hotels and movie theaters, downskilled less rapidly than other sectors.

There are two additional pieces of the decomposition that have, thus far, been ignored. The first is an ambiguous growth term that cannot neatly be classified into strictly industry mix changes or dropout intensity changes (see section 2). This term is near zero. The remainder – around 25 percent – is absorbed by higher rates of unemployment for dropouts.[27]

In short, it appears that most of the relative increase in the availability of dropout workers in these California cities and in Miami in the 1980s can be accounted for by increased use of dropouts in all different industries, with the remainder ending up in unemployment. There appears to be very little change in industry mix. Recall also that industries found productive uses for these added dropouts, as evidenced by the fact that their relative wages did not fall.

In the next section I will present evidence that this result is not particular to these cities or to dropouts. In general, changes in industry mix are not a big part of how metropolitan areas absorbed changes in worker mix during the 1980s.

5. Metropolitan Areas During the 1980s

This section uses a regression framework to ask whether changes in the skill composition in 179 US metropolitan areas during the 1980s caused accommodating changes in industry mix,

[27] At first blush this might appear to be inconsistent with the small decline in employment in Table 1, but note that the base for changes in employment rates is *all* dropouts, not just the new arrivals. Thus even a small decrease in employment rates can absorb a substantial fraction of new workers. Similar results are obtained in the next section.

or changes in the factor intensity of industries. Since this mirrors regressions used in the so-called "area analysis" approach to measuring the impact of immigration (e.g. Card (2001)), I begin by showing that changes in skill mix also appear to have little impact on wages or employment in my data. Tables 3 shows estimates of employment rate and wage elasticities derived from regressions of the form:[28]

$$\%\Delta w_{ic} \text{ or } \%\Delta\left(N/L\right)_{ic} = a_i + d_c + h\%\Delta L_{ic} + z_{ic}$$

where $\%\Delta\left(N/L\right)_{ic}$ represents the percent change in the employment/labor force and $\%\Delta w_{ic}$ represents changes in the real wage during the 1980s for education group *i* in city *c*. There are four skill groups, *i*, based on workers' self-reported final level of schooling: workers with less than a high school education, exactly a high school education, with some college education (but without a 4-year college degree), and with a bachelor's degree or more. The top panel contains elasticities estimated across 179 metropolitan areas, using an OLS regression.[29] The estimates confirm that labor supply has little impact on relative employment rates, as has been found in numerous other studies. The wage elasticity is estimated to be minus 0.03, which implies an elasticity of substitution between these groups larger than 30. Larger relative supply growth of a given education group is also not

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[28] Regressions throughout this section are weighted by $\left(P_{80}^{-1} + P_{90}^{-1}\right)^{-1/2}$.

[29] All metropolitan areas within the lower 48 states that were either among the top 100 recipients of working age foreign-born arrivals during the 1980s or had at least 1 percent of their population in 1990 arrived from a foreign country during the 1980s. Very few metropolitan areas were dropped under these criteria that would not otherwise have to be dropped because of difficulties in matching metropolitan areas across datasets. A small number of less populous metro areas in New England were dropped separately because there was no feasible way to construct them consistently using both the PUMS and ASM data.

systematically associated with a lower employment rate of that group in these cities, shown in column 2.

One concern with these estimates that can be immediately addressed is that cross-regional differences in the change in labor mix may be driven in part by differential growth in relative labor demand. To identify an exogenous component of observed changes in labor mix, I use an instrument similar to Card's (2001). It is motivated by the observation that immigrants tend to settle in areas of the US among people from their home country (Bartel (1989)). This idea can be used to create a measure of the "supply-push" component of foreign immigration, by assigning recent immigrants to the cities where their countrymen were living at some point in the past. At a point far enough in the past, it is hoped, the location of immigrants is exogenous to current demand conditions. The instrument is constructed as follows:

$$Z_{ic} = \sum_g \frac{F_{gc}^{70}}{F_g^{70}} F_{gi,85-90}^{90}$$

where $F_{gi,85-90}^{90}$ = the number of 1985-90 immigrants from country g in skill group i in 1990, and $\frac{F_{gc}^{70}}{F_g^{70}}$ = the share of immigrants from g living in city c in 1970. Thus Z_{ic} assigns recent migrants from each country to the US cities where immigrants from their home country were living in 1970. In practice, immigrants are grouped into 16 regions of origin, three of which (Cuba, the Philippines, and Mexico) are individual countries. These regions are listed in Appendix Table 1.

To make the first stage coefficients interpretable, I have divided the instrument by the average of each city's 1980 and 1990 population. Column 1 of Table 4 shows that the first-stage regression is strong, which occurs for two reasons: 1) early immigrant settlements are indeed a strong force attracting continued immigration to a particular location, even 20 years later; and 2) foreign immigration is a major force shaping demographic changes in US metropolitan areas. This table also shows regressions run separately by skill group (dropping the city fixed effect and including a control for population growth). This reveals that the instrument has a relationship with labor supply changes during the 1980s for workers with less than a 4-year college degree, but not for more-educated workers, reflecting the fact that foreign immigration to the US during the late 1980s was dominated mostly by workers with less than a 4-year degree. Only the combined first stage regression in the first column is used in the analysis that follows.

Two-stage least squares estimates of the wage and employment elasticities that use this instrument are shown in the bottom panel of Table 3. Because the instrument is only available for the subset of metropolitan areas in the 1970 Census, the middle panel shows the OLS estimates for this group of cities, which are similar to the full sample OLS estimates. The IV estimates, however, are more negative, implying that labor flows may in part be driven by local demand shocks. Wages and employment rates of workers are reduced by an increase in the local relative supply of workers with similar levels of education, but these estimates still imply that employers substitute across education types elastically. The elasticity estimates are 0.04 for employment and 0.09 for wages.

Changes in Industry Mix

Next, I ask whether a growth in the relative supply of some worker type is associated with a relative growth in the industries that employ that type of labor, motivated by empirical evaluation of equation (3). As described in section 2, in doing so it is important to control for scale effects, which also could generate such a relationship, and to account for the influence of exogenous changes in production technology that alter the relative usage of different labor types. The former is accommodated with a city fixed effect, and the latter with a skill group fixed effect. Letting c index metropolitan areas, I estimate regressions of the form:

$$(4) \qquad \sum_j s_{ijc}^{1980} \%\Delta M_{jc} \equiv y_{ic} = l_i + q_c + g\,\%\Delta L_{ic} + e_{ic}$$

…where y_{ic} is the 1980 share-weighted growth in industry scale – the expected absorption of type-i workers in city c in the 1980s – $\%\Delta L_{ic}$ is the growth of the number of workers in group i and city c and e_{ic} is an unobserved error term capturing, among other things, city- and skill-group-specific labor demand shocks, which might be correlated with $\%\Delta L_{ic}$. The coefficient of interest, g, measures the share of relative supply growth of some type of labor absorbed by changes in industry mix that favor its employment. Recall that under the strictest HO model, this will be 1. Note also that, analogous to the previous section, this has a "second difference" interpretation: it represents the fraction of the growth in the supply of some skill type relative to other skill types and relative to other cities absorbed by changes in industry mix. This interpretation arises here because of the inclusion of skill group and city fixed effects.

I begin by measuring industry growth $\%\Delta M_{jc}$ with growth in the output of manufacturing industries. This produces an estimated g of 0.03, shown in the first column of Table 5, which is to say that changes in the education composition of a metropolitan area's work force are typically associated with a change in manufacturing mix that might accommodate 3 percent – essentially none – of the supply change. This qualitative result is not particular to measuring industry growth with output. Columns 2 and 3 show similar estimates using as measures of industry size the real book value of capital stock (buildings and equipment) and employment. It is also not particular to the dataset being used. Manufacturing employment data from the Census of Population produces a similarly small estimate of 0.01.

Sectors Outside Manufacturing

While manufacturing has the advantage of being unambiguously tradable, the sector does not include an exhaustive set of traded goods. In fact, it might be quite reasonable that there is not much action in the manufacturing sector as it is a declining sector, employing less than 20 percent of workers in these metropolitan areas by 1990, a number reported in the bottom row of Table 5. Particularly for more skilled workers, there may be other traded industries that can expand to accommodate labor flows, and their omission might account for the small point estimates. To address this, I will now add other sectors. Doing so will require me henceforth to use only total employment in the Census of Population as my measure of industry size.

A challenge is to determine which sectors can be construed as tradable and therefore should be included in this sum. I know of no serious effort in the trade literature to evaluate which industries are tradable, though, among others, Hanson and Slaughter (2002) specify sectors to be considered traded and not for their analysis. In addition to manufacturing, they include agriculture, mining, finance, real estate, business services, and legal services. I will begin using this definition and then include all sectors, with the understanding that the latter may overstate the role changes in the mix of *traded* industries has in absorbing labor shocks.

Column 5 of Table 5 limits analysis to the sectors defined as traded industries by Hanson and Slaughter (2002). The bottom panel of this table shows these sectors employed about one-third of workers in both 1980 and 1990. Adding these other sectors raises the estimate of g only slightly, to 0.05, which is now distinguishable from zero. Column 6 adds all other industries to the analysis. Here again we get a positive estimate, but the overall effect is small. The 0.07 point estimate suggests that growth in the availability of some type of worker is associated with a relative growth 7 percent as large of the traded and non-traded industries that tend to employ that type of worker.

Endogeneity

The OLS estimates presented so far of the short-run industry mix response to changes in worker mix have a causal interpretation under the assumption that changes in worker mix are randomly assigned to cities. In fact, a demand shock for the output of a particular industry could tend to draw the types of workers employed in that industry to the locality: a growing apparel sector might attract dropouts, rather than vice versa. This implies that even the small positive association seen so far might merely be spurious.

To address this concern, a two-stage least squares estimate of (4) is also performed, using the instrument described above. The results of this regression are shown in the first column of Table 6. The upper panel of the table repeats the OLS estimate for all industries from the previous table (0.07), the middle panel shows the OLS estimate for the 90 cities for which the instrument is available (nearly the same – 0.08), and the bottom panel shows the IV estimate, which is slightly smaller (0.04) and only marginally statistically significant. The endogenous response of worker mix to relative industry growth thus may have contributed to a slightly positive upward bias of the industry mix response; it appears that changes in worker mix, at least those measured by education, have almost no influence on the mix of industries that matters for employment.

Other Types of Responses to Changes in Worker Mix

The framework of section 2 also provides for examination of the share of labor supply changes absorbed through changes in the skill mix of employment, holding constant industry mix, the second term of decomposition (2). I will look for evidence of that type of change by estimating the following regression:

$$\sum_j s_{ijc}^{1980} \%\Delta\left(\frac{N_{ijc}}{N_{jc}}\right) \equiv y'_{ic} = l'_i + q'_c + g'\%\Delta L_{ic} + e'_{ic}$$

In other words, I regress growth in type-*i* intensity of a typical industry (the share-weighted growth in (N_{ijc}/N_{jc})) on the growth in the type-*i* intensity of the city's labor supply. g' measures the elasticity of employment mix within industry to the local supply mix or, more simply, the share of worker mix changes absorbed within industry.

Estimates of g' are shown in the second column of Table 6. OLS estimates suggest half of all changes in labor supply are absorbed within industry, and IV estimates (using the same instrument) suggest that at least three-quarters are. (Higher concentrations of employment of a particular type of worker are negatively associated with labor inflows of that type, biasing OLS downward.) Each estimate is statistically different from 1, in part because of the small negative impact that labor supply growth has on overall employment rates, discussed further below. Another reason is that we have not yet completed the employment decomposition – there is a third term of (2) that contains the interaction of industry size and within-industry changes and cannot be assigned uniquely to either. OLS estimates of this component's share of the decomposition, shown in the third column labeled "Ambiguous" ($y''_{ic} \equiv \sum_j s_{ijc}^{1980} \%\Delta N_{jc} \cdot \%\Delta\left(\frac{N_{ijc}}{N_{jc}}\right)$ is the regression dependent variable are 0.3-0.4. In the inequality literature (e.g. Autor, Katz, and Krueger (1998)) it is customary to assign half of this term to the between-industry changes (column 1) and half to the within-industry changes (column 2) – which would imply approximately 1/3 of local labor mix changes are absorbed between industries and 2/3 within industry. However, the IV estimates for the portion that is absorbed by this "ambiguous" or residual term are considerably smaller and statistically indistinguishable from zero; this says that under any decomposition, changes in the relative supplies of different types of workers have little impact on the relative size of industries that tend to employ that type of worker. Instead, a higher relative supply of some worker type tends to lead to a nearly proportional increase of that type in relative employment within a relatively unchanged industry structure. This occurs without much change in the relative wages, as we saw in Table 3, suggesting that employers operate with a production function – or set of production functions – that allow them to trade off flexibly between different types of workers.

The Role of Unemployment

Columns 1-3 of Table 6 present a decomposition of *employment* changes on the base of changes in worker *supply*. To the extent that an increase in the relative supply of some type of worker leads to high rates of unemployment for that type (as the IV estimates in Table 3 suggested they do), then columns 1-3 of the table would need not sum to one and, in fact, they do not. The difference of the sum of columns 1-3 from one (or g''' from the regression $s_{iUc}^{1980}\%\Delta(N-L)_{ic} \equiv y_{ic}''' = l_i''' + q_c''' + g'''\%\Delta L_{ic} + e_{ic}'''$ where s_{iUc}^{1980} is the share of the type-*i* labor force unemployed in 1980) is the share of changes in relative supply absorbed by changes in overall relative employment rates. These numbers are shown in the fourth column of Table

6. OLS estimates suggest that 8 percent of changes in worker mix were absorbed by unemployment, while IV estimates suggest that almost 20 percent were. This estimate is similar to the one in the previous section, where it was found that 25 of the growth in high school dropout workers in some major California cities and in Miami were absorbed through higher relative dropout unemployment; it is also consistent with Schoeni's (1996) finding that the unemployment impact of immigration was sizable during the 1980s.

6. Changes in Computer Use and Occupation Mix

Changes in Computer Use

So far I have presented evidence that local labor mix changes are largely absorbed within industry and without much change in relative factor prices. This might occur if technology is endogenously chosen to complement local worker mix. Acemoglu (2002) suggests, for example, that the recent rise of computers in the workplace might be endogenously related to the growth in college-educated labor, which could have led the relative wages of the college-educated to rise even in the face of a large relative supply increase. To evaluate whether endogenous biased technological change could explain the lack of responsiveness of relative wages to relative labor supply, it is useful to ask whether technological change differed across cities according to changes in their mix of workers.

To evaluate this, I will use data on the prevalence of computer use in the workplace from the 1984 and 1993 computer-use supplements to the October Current Population Survey. These same data were used by Autor, Katz, and Krueger (1998), who were interested in determining whether variation (across industries) in the change in computer use led to changes in the share of more educated workers.[30] Here I want to use the data to investigate a reversed version of this hypothesis, asking whether changes in the skills of a city's work force drive variation in the uptake of computers.

I will again treat metropolitan areas as local labor markets. There are 44 metropolitan areas that can be matched between the 1984 and 1993 CPS, and there is a surprising amount of variation in the growth in the prevalence of computers across these metropolitan areas.[31] In these 44 cities, the fraction of workers who report using a computer at work climbed by 20 percentage points (from 30 percent to 50 percent) between 1983 and 1994; the standard deviation of the increase (across metro areas) is 4 percentage points.

Table 7 presents a few specifications that attempt to explain the cross-city variation in the growth in computer use with changes in labor force attributes. Column 1 shows that nearly half of the variation across cities can be explained by changes in the relative supply of four aggregate education groups (high school dropouts are excluded) and that computer use appears to be monotonically increasing in the relative supply of more educated workers. This is not by itself surprising as more educated workers are more likely to be employed at a job that uses a computer (DiNardo and Pischke (1997)). However, even after accounting for the individual tendency of more educated workers to use a computer, a city's supply of educated workers appears to affect the overall computer use rate. To see this, the regression in column 2 uses as the dependent variable the mean residuals (in each city) from an

[30] I use the question, as do they, which asks each worker whether they use a computer directly at work.
[31] These are the 44 largest metropolitan areas in 1983, with the city of Oakland treated as part of the San Francisco metropolitan area.

individual level regression of computer use on education across all 44 cities.[32] (Separate regressions are run with the 1984 and 1993 data.) Taking out this individual tendency of more educated workers to use a computer reduces but does not eliminate the effect of the relative supply of educated workers on the rate of computer use. Put another way, this says that the same individual is more likely to use a computer at work in a city where the work force is more educated.

Autor, Katz, and Krueger (1998) document that industries where computerization took place most rapidly also took on more skilled workers. My paper has investigated the role of changes in industry mix in response to supply changes. The two may be related: the high rate of computer use in cities with a more educated work force could be driven by the presence of more skilled industries. To investigate this, the regression in column 3 first residualizes computer use at the individual level in both education and industry (with an exhaustive set of dummies for the latter) before aggregating to the city level. This again reduces the coefficient on the aggregate supply measures but does not eliminate it. What this says is that there is a substantial *within*-industry component to the effect of educated labor supply on the rate of computer use.

Though merely suggestive, the observed correlations support the idea that technological change may be related to changes in local skill mix of labor supply. The association of computerization with a more educated work force suggests that variation in the pace of skill-

[32] A dummy for computer use at work was regressed on dummies for high school graduate, some college, and college graduate and a linear term for years of education. There were 24,586 observations in the 1984 regression and 23,089 in the 1993 regression in the 44 metropolitan areas.

biased technological change across cities may have had a role in mitigating the impact of relative factor supplies on wages.[33]

Changes in Occupations

A natural follow-up question to the results of this paper is to ask what added workers of a given skill type are doing within industry. To get at this, it is possible to repeat the analyses of sections 4 and 5 using occupations, rather than industries, as the unit of analysis. Results of this exercise indicate that most changes in skill mix are absorbed within occupation (0.76 share).[34] In light of the results of this paper and the fact that many occupations are tied closely to particular industries (e.g. textile sewing machine operators are employed mostly in the textile industry!) this is not a big surprise. However, it is worth pointing out for two reasons. First, to the extent that detailed occupations proxy for the mix of more finely disaggregated industries, it suggests that the industry results here are likely to be robust to further disaggregation.[35] In addition, it suggests the nature of work performed by a given skill type depends directly on that labor type's presence in the local labor market, lending some support to the idea that production technology depends on local worker mix.[36]

[33] It is worth noting that this result may also help explain why residual wages and total factor productivity are higher in labor markets with more educated workers (Moretti (2002, 2003)). If educated workers attract skill-biased technologies and these technologies are more productive, then residual wages and TFP would be higher in markets with more educated workers.
[34] Lewis (2003) performs the occupation analysis in greater detail.
[35] The Census of Population divides workers more finely into occupations than into industries.
[36] Autor, Levy, and Murnane (2003) show that the task content of occupations has changed over time. It is entirely conceivable, therefore, that the tasks performed within a given occupation may differ across markets.

7. Discussion

Reconciliation with the Trade Literature

Hanson and Slaughter (2002), using gross state product and state-level labor force data, provide evidence that large US states experienced common changes in production technique during the 1980s, after accounting for industry-neutral state-factor-specific productivity shocks, modeled by fixed effects. This is interpreted as providing support for HO modified to allow factor-specific productivity differences across localities (Trefler (1993), described below). This paper approaches the analysis from the other side of things: it shows changes in production technique *not* common across localities – the part of the variation Hanson and Slaughter remove with fixed effects – move proportionately with labor mix in that locality. The present study uses data that are both geographically and industrially more disaggregated than Hanson and Slaughter (2002), but Saad-Lessler (2003) shows even in Hanson and Slaughter's data local changes in production technique are strongly related to local changes in factor supplies. In addition, like me, Hanson and Slaughter (2002) find that changes in industry mix account for at most a small portion of local changes in worker mix.

These results bear some resemblance to Trefler's (1993) modified version of HO. He showed that once factor supplies are adjusted for local productivity differences, they could explain the cross-sectional pattern of trade flows between countries. However, the results here suggest more strongly that local *changes* in the relative productivity of different factors are what predominantly accommodate local changes in worker mix.[37] Endogenous changes

[37]It is possible to interpret this result as being consistent with a further "modified" HO theory, at some point HO ceases to be an informative theory about what generates trade flows and instead simply becomes an accounting identity. Trefler's (1993) paper is itself agnostic on the source of country-specific productivity differences, and thus tells us little about whether factor supplies in fact determine trade flows.

in production technology may underlie this: I found that the skill content of occupations responded to the local labor supply mix and that computer use grew more quickly in cities where the educated work force grew more rapidly.

Caveats

There are caveats to the present research. One is that there could be within-industry changes in product mix that are evaluated as changes in production technique at the level of aggregation used in this paper. Recent research in trade has placed emphasis on product-level heterogeneity (for example, Bernard and Jensen (2002)). While the data used in this paper are more disaggregated than those typically available to investigations of HO, 3-digit industries are by no means homogeneous. This paper did present some suggestive evidence that the bias from aggregation could be small: occupation mix, which might be construed as a proxy for more finely disaggregated industry cells, was no more responsive than industry mix.

An alternative interpretation of these results is that education is a poor proxy for worker skill. For example, a recent paper by Borjas (2003) estimates native-immigrant elasticities of substitution with comparisons between decennial censuses (using only time series rather than cross-regional comparisons). He obtains larger estimates by looking at education-work experience cells than by looking at education cells alone. The robustness of the present results to different definitions of skill is untested, though it is generally believed that the 1980 Mariel boatlift was an unskilled shock to Miami's work force, and no major changes in industry structure or labor market outcomes were apparent there (Lewis (2003), Card (1990)).

8. Conclusion

This paper finds using two different approaches and measuring industrial composition using both household and establishment data that changes in the mix of industries accommodate only a small part of the changes in the composition of local labor supply in US metropolitan areas. In low-skill immigration cities and in US cities in general changes in industry mix did not tend to favor employment of newly arriving workers during the 1980s. This suggests that the standard HO model is not a very good description of how local labor markets adjust to labor mix shocks. It would be an overstatement to interpret these results as saying a city's industry structure is unaffected by the composition of the local workforce – I found evidence, for example, that low-skill workers may attract apparel production. These results instead say that changes in industry mix are not a major source of adjustment to labor supply shocks.

This paper also shows that the hiring practices of the vast majority of industries are highly responsive to the composition of local labor supply. Cities that receive more of some type of labor increase their relative employment of that type of labor in the average industry by 80 percent as much as the citywide supply increase. The remainder ends up in higher rates of unemployment, consistent with Shoeni's (1996) finding that immigration was associated with some unemployment during the 1980s. However, the fact that large within-industry changes in worker mix are associated with little change in relative wages suggests that industries are choosing production technology to complement local factor supply mix. More direct evidence for this interpretation was found in the fact that computer use grew more rapidly in areas with a faster relative growth in the supply of educated labor.

Future research might examine in greater detail the effect of local labor mix on the use of capital with different degrees of skill-complementarity and the effect of this, in turn, on productivity. The results would have some potential to explain how local factor-specific productivity differences arise, which could form the basis for a richer model of the open economy that is consistent with the data.

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Table 1
Growth in Labor Force Attributes 1980-1990, Selected Regions

Metropolitan Area or Region	Dropout/Non Dropout… Labor Force	Employ-ment/LF	Real Wages	Immi-grant LF/Pop	*Native* d.o./non-d.o. LF	Adult Popula-tion
	(1)	(2)	(3)	(4)	(5)	(6)
Los Angeles-Long Beach, CA	0.12	-0.03	-0.23	0.69	-0.32	0.15
Anaheim-Santa Ana, CA	0.09	-0.04	-0.26	1.21	-0.38	0.28
Miami-Hialeah, FL	0.04	-0.03	-0.16	0.50	-0.30	0.10
Fresno, CA	0.03	-0.04	-0.16	0.93	-0.30	0.24
Santa Barbara, CA	0.03	-0.02	-0.26	0.89	-0.31	0.15
Salinas-Seaside-Monterey, CA	-0.03	-0.03	-0.27	0.41	-0.35	0.22
Riverside-San Bernardino, CA	-0.04	-0.03	-0.21	1.13	-0.30	0.48
(T) All "Treatment Cities"…	**0.07**	**-0.03**	**-0.22**	**0.70**	**-0.32**	**0.20**
(C) Comparison Cities†	**-0.44**	**-0.02**	**-0.20**	**0.38**	**-0.52**	**0.00**
Continental US	**-0.43**	**-0.01**	**-0.26**	**0.36**	**-0.37**	**0.16**
Treatment(T) - Comparison(C)	**0.51**	**-0.02**	**-0.02**	**0.32**	**0.20**	**0.19**
(Standard Error)	**(0.01)**	**(0.00)**	**(0.01)**	**(0.02)**	**(0.11)**	

†The comparison cities (metropolitan areas) meet the criteria that they employed high school dropouts in similar industries as the treatment cities in 1980; see text for details. The comparison cities are: Philadelphia, PA; Oakland, CA; San Diego, CA; Nassau-Suffolk, NY; St. Louis, MO; Nashville, TN; Cincinnati, OH; Middlesex-Somerset, NJ; Portland, OR; Kansas City, MO-KS; Newark, NJ; and Bergen-Passaic, NJ.

Table 2

Decomposition of Relative Growth In Dropout Labor Supply

Industry Size Measure	Fraction Absorbed.. Between Industries	Within Industry	Initial share of dropouts
	(1)	(2)	
Manufacturing			
Output	-0.04	0.37	
	(0.05)	(0.08)	
Employment	0.01	0.30	0.30
	(0.01)	(0.01)	
All Industries			
Employment	-0.12	0.83	1.00
	(0.01)	(0.02)	

Source: US Census Bureau, CES, Annual Survey of Manufactures data and 1980 and 1990 PUMS.

Table 3

Wage and Employment Elasticities Estimated Across Metropolitan Areas

	Mean Wages	Employ-ment/LF
OLS, 179 Metropolitan Areas		
Elasticity	-0.03	0.00
	(0.01)	(0.00)
R^2	0.91	0.73
OLS, 90 Metropolitan Areas		
Elasticity	-0.04	0.00
	(0.01)	(0.00)
R^2	0.94	0.75
IV, 90 Metropolitan Areas		
Elasticity	-0.09	-0.04
	(0.03)	(0.01)
R^2	0.93	0.72
Skill Group FE?	YES	YES
City FE?	YES	YES

Notes: See text for details.

Table 4

IV First Stage: Labor Supply Growth on Immigrant Labor Supply "Push" Per Capita

Dependent Variable: Education Group Specific Labor Supply Growth

	IV First Stage	First Stage Separately By Education Level: High School Dropouts	High School Graduates	College <4yr degr.	College Graduate
Imm Supply	9.05	4.32	-8.38	-25.78	-0.13
"Push"/Capita	(1.25)	(0.64)	(1.70)	(3.59)	(2.78)
Overall Pop		1.02	0.66	1.39	1.24
Growth[1]		(0.06)	(0.05)	(0.08)	(0.08)
R^2	0.93	0.82	0.73	0.82	0.75
Skill Group FE?	YES	YES	YES	YES	YES
City FE?	YES	NO	NO	NO	NO

Source: 1980, 1990 PUMS data and 1970 1% county group files. Regression run over 90 metropolitan areas. See text for details of construction of the instrument and sample.

[1]Population growth for the city as a whole, not by skill group. Labor supply growth is by skill group. Regressions weighted by $(1/P_c^{80}+1/P_c^{90})^{-1/2}$, where P_c^{80} and P_c^{90} represent the 1980 and 1990 populations of a city *c*. See text for details.

Table 5

Changes in Worker Mix Absorbed by Changes in Industry Mix, 1980-90

Sector:	Manufacturing				H&S	All
Dataset:	ASM	ASM	ASM	PUMS	PUMS	PUMS
Scale Measure:	Output	Capital*	Employment	Employment	Employment	
	(1)	(2)	(3)	(4)	(5)	(6)
			OLS, All Cities			
Labor Supply	0.03	0.01	0.04	0.01	0.05	0.07
Growth	(0.02)	(0.02)	(0.02)	(0.00)	(0.01)	(0.01)
R^2	0.86	0.86	0.83	0.91	0.93	0.98
Skill Group FE?	YES	YES	YES	YES	YES	YES
City FE?	YES	YES	YES	YES	YES	YES
			Percent Employed, This Sector			
1980	0.21	0.21	0.21	0.21	0.36	1.00
1990	0.16	0.16	0.16	0.16	0.33	1.00

Source: US Census Bureau, CES, Annual Survey of Manufactures and 1980, 1990 PUMS. Labor supply growth is by skill group. Average of 1979-81 observations taken for 1980 observation. Regressions weighted by $(1/P_c^{80}+1/P_c^{90})^{-1/2}$, where P_c^{80} and P_c^{90} represent the 1980 and 1990 populations of a city c. *Measured to 1992. See text for details.

Table 6
OLS, IV Estimates of Decomposition of Changes in Worker Mix

	Between Industry	Within Industry	Ambig-uous	Unem-ployment
	OLS, All Cities			
Labor Supply Growth	0.07	0.45	0.42	0.08
	(0.01)	(0.02)	(0.02)	(0.01)
R^2	0.95	0.97	0.75	0.83
	OLS -- 90 IV Cities			
Labor Supply Growth	0.08	0.52	0.32	0.08
	(0.01)	(0.02)	(0.03)	(0.01)
R^2	0.99	0.97	0.64	0.84
	IV			
Labor Supply Growth	0.04	0.74	0.08	0.17
	(0.02)	(0.06)	(0.07)	(0.02)
R^2	0.99	0.97	0.47	0.76
Skill Group FE?	YES	YES	YES	YES
City FE?	YES	YES	YES	YES

<u>Source</u>: 1980, 1990 PUMS.

Table 7

Impact of Labor Force Changes on Changes in Computer Use, 1984-1993

Change in ….	(1)	(2)	(3)
High School Grad	0.05	0.04	-0.12
LF/Capita	(0.17)	(0.17)	(0.13)
Some College	0.58	0.43	0.22
LF/Capita	(0.18)	(0.18)	(0.14)
College Graduate	0.74	0.40	0.22
LF/Capita	(0.15)	(0.15)	(0.11)
Residualized in Individual Level…			
Education[1]	NO	YES	YES
Industry[2]	NO	NO	YES
R^2	0.48	0.25	0.18
N Cities	44	44	44

Source: 1984 and 1993 October Current Population Surveys; "Computer use" represents fraction of workers who report directly using a computer at work. Standard errors in parentheses. [1]Individual level regression include a dummy for high school grad, some college, college grad and a linear term in years of education. [2]Industry controls are an exhaustive set of dummies for Census of Population (approx 3 digit) industries.

Figure 1

Index of 1980-90 Relative Growth In Manufacturing Output, by Industry*

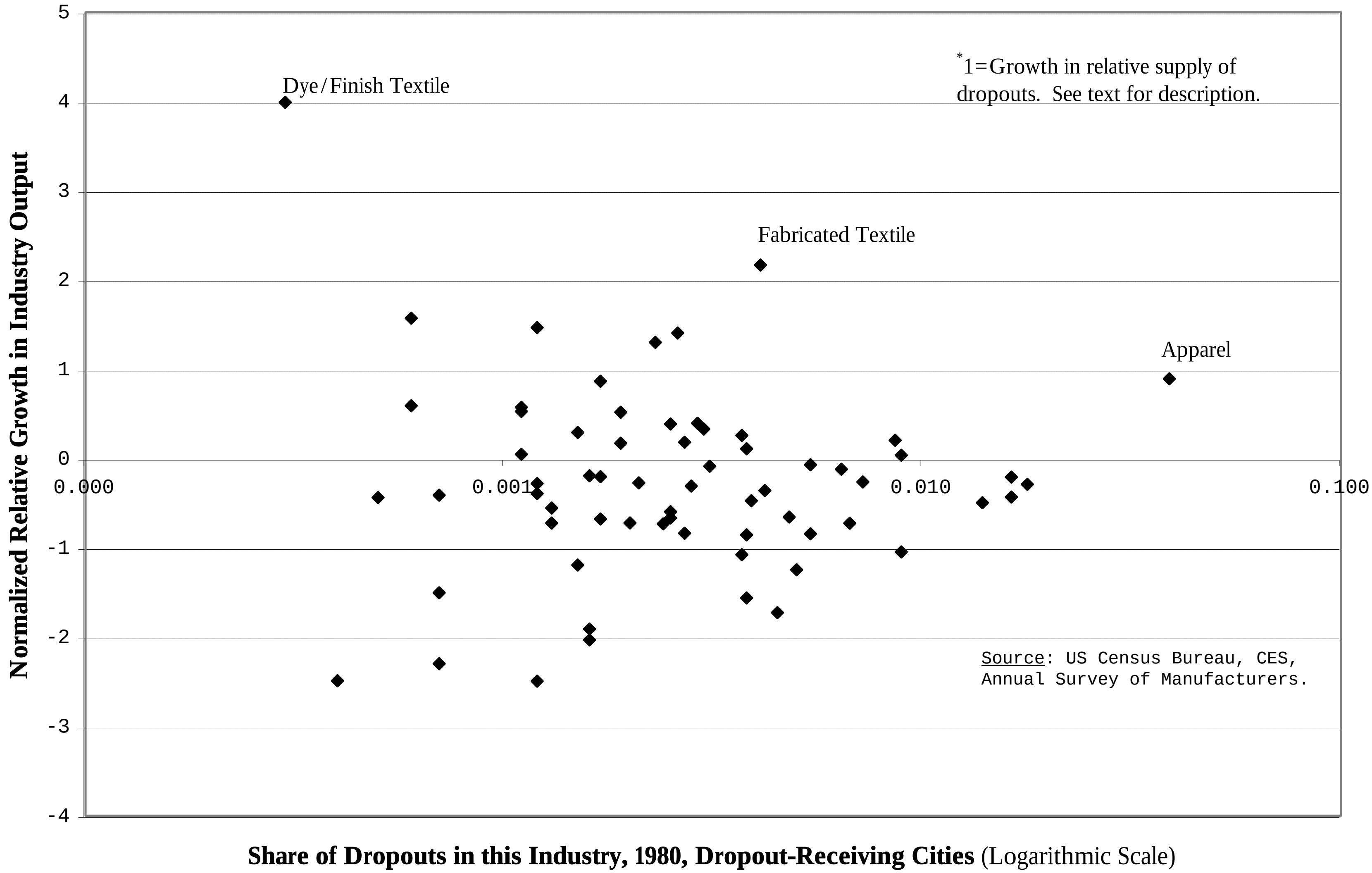


Figure 2

Index of 1980-90 Growth in Manufacturing Employment, by Industry*

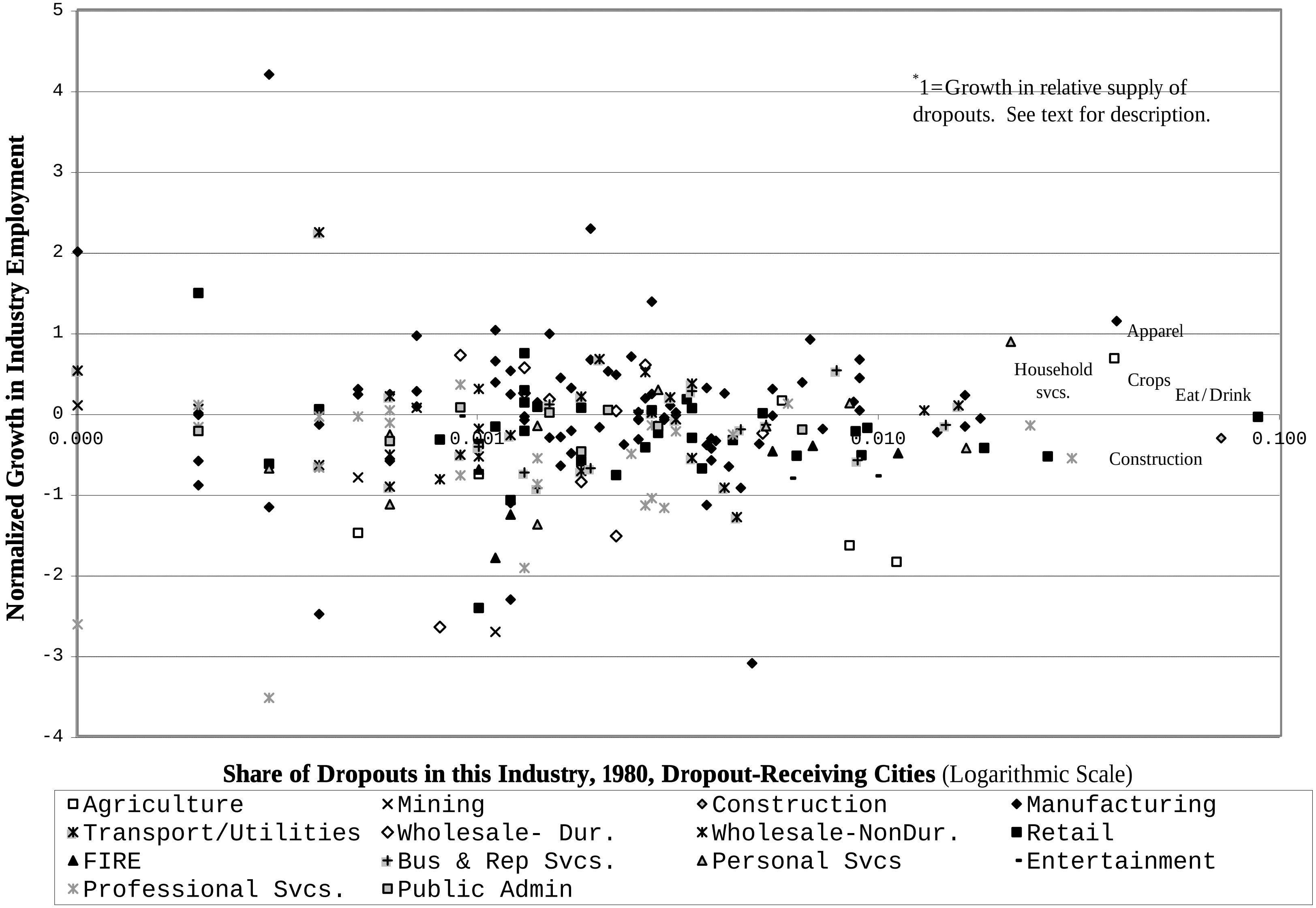
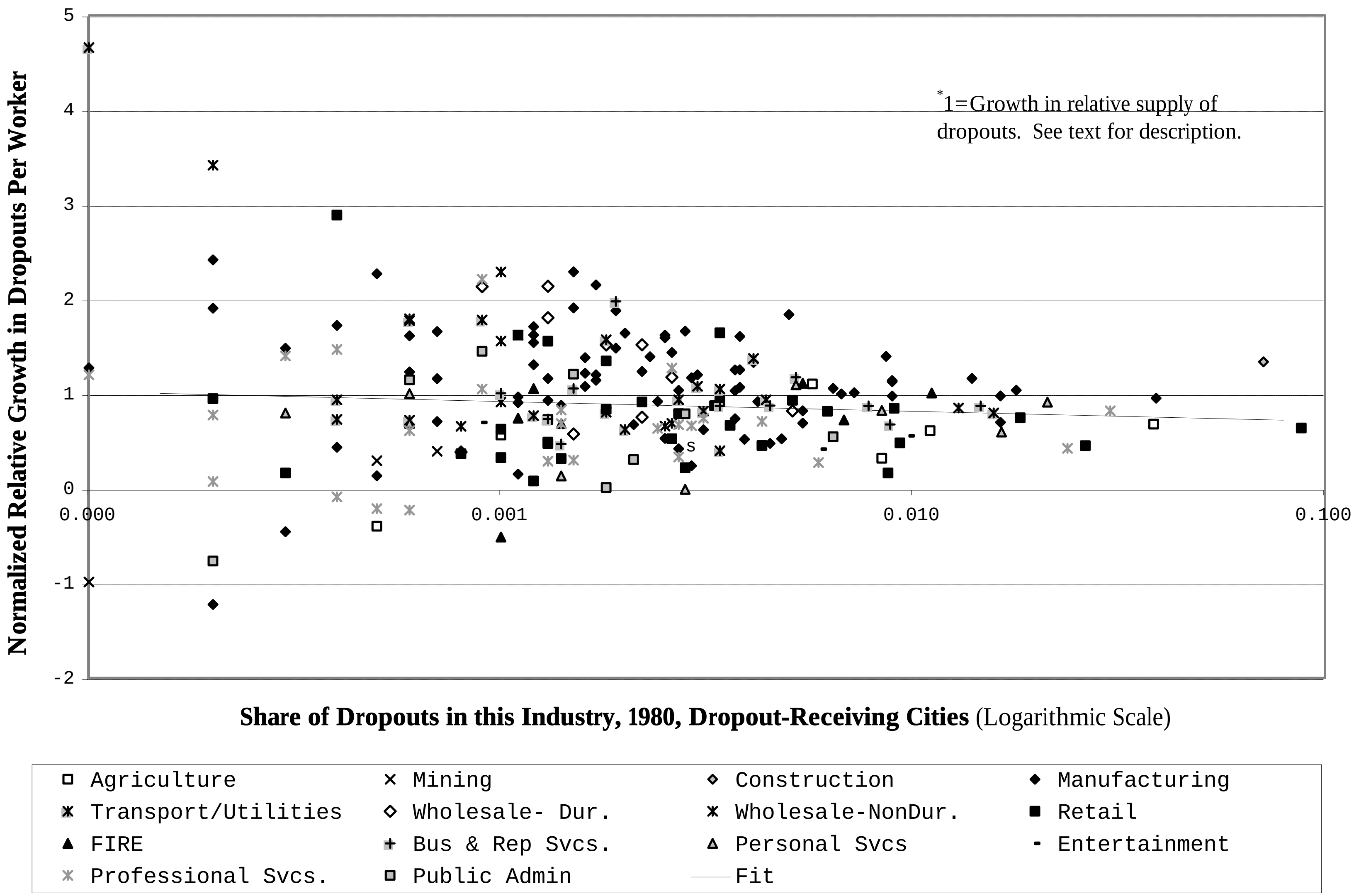


Figure 3

Index of 1980-90 Growth in Dropouts per Worker, by Industry*



Data Appendix

1. Linking Data Sources by Industry

Several links between data sets are made in order to carry this project. These come in two classes: links by industry and links by geography. Industry matches between the ASM and the labor force data are necessary because the ASM has no information on worker skills. In the ASM, establishments are classified into SIC industries based upon the products they produce. In the PUMS data, industry is for the most part determined by a worker's self-report of their primary industry of employment.[1] The Census Bureau attempts to match respondents' self-reported industry in the Census to a (usually) three-digit SIC industry but is still left with a few manufacturing categories that have no equivalent in the ASM, as they describe workers as being part of an unspecified industry within an aggregate manufacturing category (such as "Not Specified Food" and "Not Specified Machinery"). These industries are dropped for the purposes of classifying the skill content of each industry. Implicitly, this assumes that workers in the unspecified aggregates are distributed across the relevant specific industries in the same manner as those who report them.[2]

2. Linking Data Sources by Metropolitan Area

Links by metropolitan areas (MAs) are made with labor force and population data to the ASM and with each of these across time. In the ASM, an establishment's county and in some cases more detailed geographic location are reported, which is sufficient to determine their metropolitan area. The population data aren't as specific, but it is still possible to construct metropolitan areas with close geographic consistency between the data sets. In the 1990 PUMS the smallest geographic unit is the "Public Use Micro Area," (PUMA) and in the 1980 and 1970 PUMS the smallest geographic unit is the "county group." The borders of these units, which change from one census to another, do not necessarily exactly overlap with those of metropolitan areas. The present paper constructs MAs from the 1980 and 1990 PUMS using tabulations from Deaton and Lubotsky (2003), who attempt to match as closely as possible the 1990 boundaries of MAs. They find in most cases the match is fairly close.[3] A worker is counted as being in an MA if he or she reports one of the component PUMAs as his place of *residence*, since place of work PUMA is missing or not as detailed for many workers in the 1990 PUMS. When total worker counts by metropolitan area in the 1980 PUMS constructed using work PUMA are plotted against worker counts constructed using residence PUMA, the points lie tightly on a 45 degree line.

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1 In some cases a respondent's industry is actually determined by looking up the industry of classification of the employer location the respondent claims to work at. In most cases, however, the self-reported industry is recorded.

2 An additional issue is linking 1980 and 1990 PUMS data by industry and by occupation. There were some changes in industry classifications between the two years, but other than a small increase in the number of "unspecified" categories, an exact correspondence can be generated between the two by using the 1980 classifications. This is what I do. For occupations, the 1980 data are more detailed, but an exact match to more aggregated 1990 categories can be found in all cases. The occupational match is aided by the fact that the same occupational classification system underlies both the 1980 and 1990 censuses.

3 Jaeger, Loeb, and Bound (1998) also analyze extensively how well MSAs can be matched in between 1970, 1980 and 1990 versions of census public-use microdata.

In the 1970 data, MAs are constructed from groups of counties that roughly approximate the county components of the same MAs in their *1970* definition, using code similar to Altonji and Card's (1991). This means that the match isn't quite as good, but the larger inconsistency is tolerable because the 1970 data are used only for the construction of an instrument for labor supply changes based upon where immigrants were living in 1970. What is largely missing from these 1970 county groups is the outer counties of the modern metropolitan areas, which were relatively unpopulated in 1970. There are also some cases of MAs splitting into two since 1970, in which case the match is to the larger 1990 MA. In any case, the inaccuracy of the geography should not bias the results, although it may weaken the first stage. The instrument is discussed in detail in section 5.

Appendix Table 1
Education Distribution of Recent Immigrants, by Country Group

	Volume of 1985-90 Immigration	Share of 1985-90 Immigrants			
		HS Dropouts	HS Graduates	Some College	College Graduates
Mexico	921,920	0.77	0.13	0.07	0.03
Caribbean	179,540	0.48	0.25	0.19	0.07
Central America	288,960	0.67	0.17	0.11	0.06
China, HK, Singapore	210,960	0.27	0.17	0.16	0.40
South America	207,000	0.32	0.29	0.21	0.19
SE Asia / Pac. Island	195,200	0.54	0.17	0.18	0.12
Korea & Japan	197,840	0.17	0.25	0.19	0.40
Philippines	170,300	0.20	0.17	0.22	0.41
Canada, Aust / NZ / UK etc.	151,380	0.14	0.23	0.29	0.35
India, Pakistan, Centr Asia	144,460	0.20	0.15	0.16	0.50
Russia & Eastern Europe	134,400	0.25	0.28	0.19	0.29
Southwestern Europe	54,020	0.40	0.22	0.17	0.21
Northern Europe & Israel	119,820	0.16	0.22	0.25	0.37
Turkey, N. Africa, Middle East	116,720	0.22	0.22	0.24	0.32
Other Africa	59,840	0.21	0.21	0.28	0.31
Cuba	33,080	0.58	0.20	0.13	0.09

Source: 1990 PUMS