People and Machines
A Look at the Evolving Relationship Between Capital and Skill In Manufacturing 1860-1930 Using Immigration Shocks*

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Abstract

This paper empirically tests if the Second Industrial Revolution changed the way inputs were used in the manufacturing sector, and if this helped absorb skill mix changes induced by immigration. In particular, it estimates the impact of immigration-induced skill mix changes on input ratios within manufacturing industries using variation across U.S. counties between 1860 and 1930. The evidence suggests that manufacturing production functions were strongly altered over the period under study: capital began as a q-complement for skilled and unskilled workers, and then dramatically increased its relative complementary with skilled workers around 1890. Simulations of a parametric production function calibrated to our estimates imply the level of capital-skill complementarity after 1890 likely allowed the U.S. economy to absorb the large wave of less-skilled immigration with a modest decline in less-skilled relative wages. This would not have been possible under the older production technology.

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1 Introduction

Rising inequality and persistently high unemployment are once again raising concerns that technological change is outpacing many workers' ability to adapt to it (Bryjolfsson and McAffee, 2011).[1] These concerns echo with stunning similarity those of earlier times of disruption, including the Great Depression (e.g., Jerome, 1934; Keynes, 2008) and industrialization (e.g., Marx, 1932). Indeed, the conventional view is that the sorts of changes now leading to greater inequality have been ongoing since at least the early twentieth century (Goldin and Katz, 1998), and possibly even earlier (Katz and Margo, 2013). In this view, capital-skill complementarity, combined with the falling relative cost of capital (which embodies much of technological change), have pushed up relative demand for skilled labor.[2] In modern times this is thought to be due to advances in computers (e.g., Autor, Levy and Murnane, 2003), but in an earlier era, qualitatively similar patterns of mechanization, driven primarily by the spread of electricity, may have relatively benefitted skilled workers (e.g., Gray, 2013; Jerome, 1934).[3]

Is this conventional view correct? This project revisits the origins of capital-skill complementarity using a common data source and identification strategy across the period both before and after the mechanization of manufacturing, starting in the mid-nineteenth century and finishing right before the Second World War.[4] Following the literature on technology and firms during the period we study, we focus solely on the manufacturing sector.[5] To identify the level of complementarity between skill and capital, we exploit the predictable effect that large waves of immigration (and, implicitly, immigration restrictions) in the nineteenth and early twentieth century had on each U.S. county's skill mix, and ask how capital intensity (among other markers

[1] See also "The Future of Jobs: The Onrushing Wave," *The Economist*, January 2014.

[2] In this view, the reason inequality in the U.S. has not always been on an upward trajectory is that at some times in U.S. history this demand trend has been offset by rising education levels (Goldin and Katz, 2008).

[3] We are glossing over the view that recent – and possibly past – technological change was "polarizing," rather than purely inequality increasing (e.g., Acemoglu and Autor, 2011; Autor et al., 2003; Goos and Manning, 2007; Gray, 2013; Katz and Margo, 2013). In principle, our approach will allow us to investigate that possibility as well.

[4] Much existing research supports the idea that technical change in nineteenth century manufacturing was different: the early factory system was more capital and unskilled-intensive than production by artisans, and so its spread led effectively to a period of capital-skill substitutability and "deskilling" (see, e.g., Atack, Bateman and Margo, 2004). In the insightful description of Goldin and Katz (1998), all production modes exhibit capital-skill complementarity, but the switch between artisan and factory modes of production generated a period in which capital and skill were effectively substitutes in the aggregate. Indeed, one reason it is hypothesized that the North industrialized first is that it effectively had a greater relative supply of low-skill workers, in the former of women and children (Goldin and Sokoloff, 1984). The high productivity of women and children in agriculture sector in the South, in contrast, reduced their supply to the manufacturing sector. However, in contrast, one recent study finds evidence that a version of the wage "polarization" that has typified modern technological change may also have been present in the nineteenth century (Katz and Margo, 2013).

[5] This is an important caveat because technical change outside the sector may have been different (Katz and Margo, 2013). However, we believe the manufacturing sector is important in the period we are examining because its evolution seems to be closely related to the exact technological innovations that have been mentioned in the literature as the drivers of the changes around the turn of the twentieth century.

of production technology) of the industries in the area responded.[6] We do not rely on actual regional patterns of immigration, but instead use an "ethnic enclave" or "shift-share" style instrumental variables strategy which essentially imputes the impact of immigration on skill mix based on apportioning national arrivals, by origin, to their "ethnic enclaves" in a base year.[7] This strategy has been used successfully in modern immigration research (e.g., Card, 2001; Cortes, 2008), but until recently, has seen little application in historical data (though see Goldin, 1994). Our approach is facilitated by manufacturing sector data we have entered from tabulations of Censuses of Manufactures at the county/city and industry level from 1860 to 1940, and by skill mix and immigration data at the county level measured using Censuses of Population (Ruggles, Alexander, Genadek, Goeken, Schroeder and Sobek, 2010).[8] This allows us to investigate whether, if we go back far enough in time, skilled arrivals to an area ever induced local manufacturing plants to decrease their capital intensity, consistent with capital and skill being substitutes, rather than increase their capital intensity, consistent with them being complements as they have found to be in modern manufacturing data.[9]

The use of immigration-induced variation is also not just incidental: the second aim of this project is to ask whether the impacts of the waves of immigration of the nineteenth and early twentieth century differed in the context of a much different set of production choices and capital markets. In theory, the nature of production technology determines how much immigration affects relative wages. It has been shown, for example, that the impacts of immigration-driven skill mix changes on relative wages can be substantially muted when capital complements skill compared to when it does not (e.g., Lewis, 2013).[10] The relative wage impacts of skill mix shocks may also be muted during periods when modes of production of substantially different factor intensities overlap, such as, potentially, artisanal and factory production (Beaudry, Doms and Lewis, 2010; Caselli and Coleman, 2006). To test these ideas, we therefore turn to an era in which the set of production choices may have been quite different from modern times, even while concerns about the impact of technological change and immigration were quite similar to modern times, motivating our interest.

[6]This approach parallels the approach of Lewis (2011) used in modern manufacturing data, and Lafortune, Tessada and Gonzalez-Velosa (2013) in historical agricultural data. The use of regional differences in skill mix to identify capital-skill complementarity goes back to at least Griliches (1969).

[7]Specifically, we use 1850 as a base year for 1860-80, and 1880 as a base year for 1890-1940. We also include the impact of aggregate trends in the literacy rates of native-born works in each state, apportioned similarly to the county level as additional "origin" using fixed settlement patterns from the base year.

[8]1890 skills and immigration derive from published tabulations of the Census of Population from that year – see Data Appendix. Conveniently, the timing of population and manufacturing censuses coincides nearly exactly over much of this period, never differing by more than a year. Starting in the twentieth century, the manufacturing census was taken every five years; we are not using these "off year" censuses except as a data quality check in some cases.

[9]No information on capital is available after the 1919 Census, so we use horsepower as a proxy after 1919.

[10]Assuming capital is supplied elastically and complements skill, the fixed rental rates for capital mute relative wage variation driven by labor supply shocks. To see why, note that in a simple closed economy model, an influx of low skill immigrants lowers the relative wages of low skill workers in the short run. In the long run, this induces a decline in capital intensity, which raises the relative wage of low skill workers.

The data we constructed allow us to control for detailed industry effects, thus removing any confounding factors such as changes in the production mix or other structural trends. In other words, we are able to examine changes in factor intensity *within* industry in our preferred specification.[11]

Our instrumental variables estimates suggest that immigration had a significant impact on skill ratios – literacy rates – in local labor markets.[12] Furthermore, capital intensity responded to changing skill intensity, and its response changed over time. 1860-1880, capital's response was consistent with it being a q-complement of both skilled and unskilled labor, and, unlike today, the complementarity was stronger with unskilled labor. This changed dramatically during the period 1890-1930, when capital became relatively more complementary with skilled labor (consistent with previous research on early twentieth century manufacturing Goldin and Katz (1998)) and a q-substitute for unskilled labor.[13] Shifts in industry mix have a negligible in either set of results.[14] Despite the fact that we therefore find that immigration induces large within-industry changes in skill ratios, simulations of a parametric production function calibrated to our estimates suggest the flood of less-skilled immigrants from the turn of the twentieth century likely had a modest impact on less-skilled relative wages (a 7% decline), as they were mitigated by a substitution away from capital-intensive production.[15] In contrast, under the older production technology in which capital was not a substitute for, but a complement of low-skill labor, the same immigration wave would have pushed down low-skilled relative wages severely (perhaps as much as 35%).

1.1 Background

Immigrants have shaped the U.S. manufacturing sector throughout its history. From Samuel Slater memorizing and bringing the plans for textile machines to the U.S., to the skilled British and other European artisans of the nineteenth century, and finally to the masses of less-skilled

[11]This also allows another motivation for this analysis: we can use our approach to ask whether shifts in industry mix are an important source of adjustment to immigration-driven skill mix shocks. Simple small, open economy models predict that shifts in input mix will be absorbed, at least in part, by changes in traded industry mix (see, e.g., Leamer, 1995). Although this sort of model enjoys little empirical support in modern data, one study finds strong support for it in agricultural data from this era (Lafortune et al., 2013), reopening this question.

[12]Although this first result is very basic, it is also important. Without it – if, as it has been suggested, U.S. labor markets at this time were highly geographically integrated by inter-city migration (Rosenbloom, 2002) – our approach would not be feasible.

[13]The response of capital we estimate is not always statistically significant, however.

[14]This reinforces that the significant response of industry mix in the agriculture sector to immigration during this period (Lafortune et al., 2013) has to do with the lack of specificity of capital in agriculture, rather than something else about this period.

[15]We have also directly estimated the impact of immigration on the wage structure using the wage gap between "salaried officials" and "wage workers" in the census of manufacturing data, which is available starting in 1890, and found no significant relationship. However, at best this provides a noisy proxy for relative wages and these estimates are confounded by direct compositional impacts of immigration.

immigrant labor filling factories, immigrants have consistently played a prominent role in U.S. manufacturing (e.g., Berthoff, 1953). Interestingly, a prominent contemporaneous account of early twentieth century manufacturing states that its main initial motivation was to investigate how well mechanization had allowed the manufacturing sector to adapt to the severe immigration restrictions of the mid-1920s (Jerome, 1934).[16] The study's purpose was later shifted to include an investigation of the contribution of technological change to unemployment. This was of heightened concern during the Great Depression, when the study was completed, but it comes up continually and is being raised again in today's relatively high unemployment environment (Brynjolfsson and McAffee, 2011).

The two motivations for Jerome's study are really two sides of the same coin: new technologies have different skill requirements, and immigration (or its restriction) can shift the set of skills available. Many have argued the arrival of factories reduced demand for skilled artisan labor and but raised demand for less-skilled production workers performing simple, repetitive tasks. For example, Atack et al. (2004) found using 1850-80 data that larger manufacturing plants - an indicator of factory (non-artisanal) production –paid lower wages, an indicator of lower average skill. On the flip side, it is the availability of less-skilled labor to fill factories that enabled the adoption of factory production. In particular, Goldin and Sokoloff (1984) argue that such labor was only readily available in Northern U.S. in the mid-nineteenth century, which is why the north industrialized first.[17] Kim (2007) shows that in 1850-1880, U.S. counties with higher immigrant density had larger manufacturing establishments. Chandler (1977) argues that modern manufacturing required professional management, and you also see evidence of a shift to more "white collar" jobs in the late nineteenth century (Katz and Margo, 2013).

After the switch to factory production from an artisanal system, manufacturing is thought to have begun, perhaps somewhere around the turn of the twentieth century, a switch to continuous production system relying increasingly on electricity and large (more recently, automated) machinery, which Jerome called "mechanization."[18] The exact timing may have differed by industry, and of particular interest to us, location.[19] Goldin and Katz (1998) argue and provide evidence that the latter change is associated with greater skill and capital requirements, and so

[16] On page 3, Jerome states "Our survey had its origin in the hectic years of the post-War decade as an inquiry into the extent to which the effects of immigration restriction upon the supply of labor were likely to be offset by an increasing use of labor-saving machinery".

[17] Women and children initially filled such factories; in the South, in contrast, women and children's labor was already demanded by agriculture. Rosenbloom (2002) makes a similar argument about the latter half of the nineteenth century: he argues a shortage of skilled labor in local markets might of pushed producers towards adopting more labor-intensive methods (e.g., p. 87).

[18] Goldin and Katz (1998) present a slightly richer evolution in which the assembly line is another step between factories and mechanized continuous production.

[19] As an example of cross-industry heterogeneity, Berthoff (1953) describes how machines for weaving cotton textiles were developed much earlier than those for weaving woolen textiles. Similarly, Jerome's surveys suggest that steel and iron adopted mechanized production methods earlier than other industries. In terms of regional heterogeneity, Jerome (1934) found considerable cross-state variation in industrial power use, which is also the variation that Gray (2013) relies on in her study on the impact of mechanization on skill demand.

capital and skill became complementary by the early twentieth century, as they continue to be in modern times (e.g., Griliches, 1969; Lewis, 2011). They show that industries with greater capital- and electricity intensity had higher average production wages in 1919 and 1929, and had more educated workers in 1939. There are some different, or perhaps more nuanced, views of what mechanization did to skill requirements. Gray (2013) found that states which electrified more saw large relative increases in the employment of non-production workers, but among production workers decreases in the proportion of jobs requiring "dexterity" - which includes craftsman - relative to those requiring manual labor. She argues the overall effect was to "polarize" labor demand, as craftsmen were likely in the middle of the wage distribution. In contrast, Jerome (1934) argued that conveyer belts and other handling technologies may have reduced demand for manual labor.

Goldin and Katz (1998) argue that factory output substituted for the less capital-intensive artisanal production. Though this is a sensible view, the evidence for it is quite limited. One exception is James and Skinner (1985), who show that in 1850 capital and labor are more substitutable in manufacturing sectors that appear to be more skill-intensive than in sectors that appear to be less skill-intensive.

Many of the studies above use variation in some technology-use measure - the right-hand side variable - to estimate the response of skill measures. We examine the other side of the coin: how immigration-induced changes in skill mix are associated with adjustments in various measures of technology use. As the theory section will describe, both approaches should reveal the nature of the complementarity between technology and skills. Our approach will also give insight in the ability of the economy to "absorb" large immigrant inflows, as adjustments to technology can help mitigate the impact of immigration on the wages of native-born workers (Lewis, 2013).

There is another way in which the economy may have absorbed immigrants: immigrants may shift the industry mix, as Heckscher-Ohlin (HO) trade theory would suggest. In early twentieth century agriculture, for example, Lafortune et al. (2013) find evidence that immigration shifted the mix of crops towards more labor-intensive ones. This is interesting per se because, in the extreme case where HO fully holds, an economy can adjust to skill mix changes without any long-run impact on the wage structure; more generally, such adjustments mitigate the wage impact of immigration. In addition, changes in industry mix may confound changes in production technology: to the extent that production technology differs across industries, an impact of immigration on industry mix may make it (spuriously) appear that production technology has shifted at an aggregate level. The solution is to examine changes in production technology within detailed industries – in other words, to hold industry constant – a purpose which motivates our data collection, described below. Before turning to that, however, we describe a theoretical approach will motivate our empirical approach.

2 Theoretical Framework

Our work starts from a simple framework that considers a single (aggregate) production function with three production factors: capital (K), high skilled labor (H) and low skilled labor (L), which is a common formulation both in the immigration and the technology adoption literatures (see for, exampleLewis (2011) and Lewis (2013)), so let $Y = g(H, L, K)$, where Y is aggregate output.[20] We assume the production function is constant returns to scale and satisfies standard quasi-concavity constraints ($g_j < 0$ and $g_{jj} < 0 \; \forall \; j \in \{H, L, K\}$). Throughout we also assume that the capital is supplied elastically to that production method and that the interest rate is fixed at the economy level. Under these assumptions, the capital stock adjusts to maintain equality between its marginal product and the cost of capital, which implies that in equilibrium $d\ln\left(\frac{\partial Y}{\partial K}\right) = 0$. Under constant returns to scale, this translates into,[21]

$$d\ln K = \frac{L\frac{\partial^2 Y}{\partial K \partial L}}{H\frac{\partial^2 Y}{\partial K \partial H} + L\frac{\partial^2 Y}{\partial K \partial L}} d\ln L + \frac{H\frac{\partial^2 Y}{\partial K \partial H}}{H\frac{\partial^2 Y}{\partial K \partial H} + L\frac{\partial^2 Y}{\partial K \partial L}} d\ln H \tag{1}$$

Substracting $d\ln L$ from both sides of this, we derive the following expression, which describes the impact of a change in the endowment of high-to-low-skilled workers on the capital-to-low-skilled labor ratio:

$$d\ln(K/L) = \frac{H\frac{\partial^2 Y}{\partial K \partial H}}{L\frac{\partial^2 Y}{\partial K \partial L} + H\frac{\partial^2 Y}{\partial K \partial H}} d\ln(H/L) \tag{2}$$

The denominator in equation (2) is positive if the production function displays decreasing returns to capital, which was assumed. Therefore, the sign of the numerator indicates input complementarity with high skill labor: capital and high skill labor are "q-complements" if $\frac{\partial^2 Y}{\partial K \partial H} > 0$ and "q-substitutes" if $\frac{\partial^2 Y}{\partial K \partial H} < 0$. One can also subtract $d\ln H$ from both sides to derive a symmetric expression for the complementarity between capital and low skill labor from the response of the capital-to-high-skill labor ratio to changes in the relative endowment of high skill workers. The problem with this approach in the present context, is that it is not robust to mismeasurement of who is high and low skill, which is a serious concern in the economic census data we will use (which at best contains only crude cuts of "skill."). If our empirical definition of "L" in the left-hand side of (2) included some high skill workers, what we would get instead is a weighted average of the complementarity between capital and high and capital and low skill labor. What's worse, in the earliest census data we have, we can observe only the total workforce,

[20]Individual labor markets, c, may differ in overall TFP, say $Y_c = A_c * g(H, L, K)$, where A_c is TFP, but otherwise have identical production functions.

[21]The total derivative $d\ln\left(\frac{\partial Y}{\partial K}\right) = d\ln g_K$ can be written out as $\frac{Hg_{KH}}{g_K} d\ln H + \frac{Lg_{KL}}{g_K} d\ln L + \frac{Kg_{KK}}{g_K} d\ln K$. Set this equal to zero and solve for $d\ln K = -\frac{Hg_{KH}}{Kg_{KK}} d\ln H - \frac{Lg_{KL}}{Kg_{KK}} d\ln L$. By homogeneity $-Kg_{KK} = Hg_{KH} + Lg_{KL}$, which when substituted in produces expression (1). Also, as it is assumed that $g_{KK} < 0$, the denominator is positive.

$N = L + H$. Defining $\phi_h = H/N$, the share of workers who are high skill, the best we can observe in these years is:

$$d\ln(K/N) = \frac{-\phi_h L\frac{\partial^2 Y}{\partial K \partial L} + (1-\phi_h)H\frac{\partial^2 Y}{\partial K \partial H}}{L\frac{\partial^2 Y}{\partial K \partial L} + H\frac{\partial^2 Y}{\partial K \partial H}} d\ln(H/L) = \left(\frac{H\frac{\partial^2 Y}{\partial K \partial H}}{L\frac{\partial^2 Y}{\partial K \partial L} + H\frac{\partial^2 Y}{\partial K \partial H}} - \phi_h\right) d\ln(H/L) \quad (3)$$

Note that this relationship is not dispositive for the level of complementarity between capital and either type of labor. However, comparing it with ϕ_h will indicate us whether capital and high-skill labor are complementary or substitutes and the relative degree of that relationship compared to that of low-skill workers.

We can also obtain similar information by evaluating the response of the capital-output ratio which in this case is given by:

$$d\ln(K/Y) = \frac{s_L H\frac{\partial^2 Y}{\partial K \partial H} - s_H L\frac{\partial^2 Y}{\partial K \partial L}}{L\frac{\partial^2 Y}{\partial K \partial L} + H\frac{\partial^2 Y}{\partial K \partial H}} d\ln(H/L) \quad (4)$$

where $s_H = H\frac{\partial Y}{\partial H}/\mathrm{Y}$ is high-skill labor's output share and $s_L = L\frac{\partial Y}{\partial L}/\mathrm{Y}$ is the low-skill's share. If capital is particularly complementary to low-skill labor, we would thus anticipate a large negative response of the capital-output ratio to an increase in the skill ratio. If capital is particularly complementary to high-skill labor, on the other hand, we would expect a smaller negative or even a positive number.

The relationship of capital with the two types of labor is important, not only because we seek to better understand how this relationship has evolved over time but also because it has clear implication for wage adjustments. This can be seen explicitly by rewriting (4) as

$$d\ln(K/Y) = Y s_H s_L \frac{\frac{\partial \ln(W_H/W_L)}{\partial K}}{H\frac{\partial^2 Y}{\partial K \partial H} + L\frac{\partial^2 Y}{\partial K \partial L}} d\ln(H/L) \quad (5)$$

The numerator of (5) contains the response of high-skill relative wages (with $W_H = \partial Y/\partial H$ and $W_L = \partial Y/\partial L$), assuming workers are paid their marginal product, to capital, which has the same sign as the response of capital-output ratios to increases in high-skill relative supply. (5) is an explicit reminder us that complementarities work in both directions: the estimated response of the capital-to-output ratio to changes in relative skill supply also reveals the other side of the coin, how capital adoption affects relative skill demand. This is useful, as actual measures of of the wage structure are quite crude during this era.

Indeed, our estimates of the relationships above could be used to learn something about the likely magnitude of the response of relative wage to changes in skill endowments. A simple derivative identity reveals that

$$\frac{d\ln(W_H/W_L)}{d\ln(H/L)} = \frac{\partial \ln(W_H/W_L)}{\partial \ln(H/L)} + \frac{\partial \ln(W_H/W_L)}{\partial \ln K}\frac{\partial \ln K}{\partial \ln(H/L)}, \tag{6}$$

where $\frac{\partial \ln(W_H/W_L)}{\partial \ln(L/H)}$ represents the short-run (capital fixed) relative wage adjustment to a change in relative skill supply, which is negative. Note that this expression implies that the long-run relative wage impacts of a change in skill ratios (say, induced by immigration) may be smaller or larger than this depending on the relative complementarity of capital with skill. If capital complements skilled labor relative to unskilled labor – if the response in (5) is positive, so that $\frac{\partial \ln(W_H/W_L)}{\partial \ln K} > 0$ and $\frac{\partial \ln K}{\partial \ln(H/L)} > 0$ – then the long-run response of relative wages to immigration is diminished by the adjustment of capital.[22] Relative wage impacts are larger than this when capital is skill neutral. Two specific contrasting examples of prominently used production functions may be helpful in delineating this point. It is common for studies of the modern-day labor market impact of immigration to model labor demand using a constant elasticity of substitution (CES) production function featuring separable capital, like $K^{\gamma}\left(H^{\frac{\sigma-1}{\sigma}} + L^{\frac{\sigma-1}{\sigma}}\right)^{\frac{(1-\gamma)\sigma}{\sigma-1}}$. In such a setup, capital's share is fixed at γ and

$$\frac{d\ln(W_H/W_L)}{d\ln(H/L)} = \frac{\partial \ln(W_H/W_L)}{\partial \ln(H/L)} = -1/\sigma \tag{7}$$

Put differently, the response of relative wages to relative supply estimates of the inverse elasticity of substitution between H and L which, more the point, is unaffected by the adjustment of capital. At another extreme, in the CES production function featuring capital-skill complementarity in Autor et al. (2003), $\left((K+L)^{\frac{\sigma-1}{\sigma}} + H^{\frac{\sigma-1}{\sigma}}\right)^{\frac{\sigma}{\sigma-1}}$, even if the elasticity of substitution between and H and L remains the same (σ), the long-run relationship $\frac{d\ln(W_H/W_L)}{d\ln(H/L)} = 0$ as skill mix changes are entirely absorbed by adjustments in capital. Intuitively, fixed rental rates for capital pin down the price of labor inputs, as capital and low-skill labor are perfect substitutes in this extreme form of capital-skill complementarity.

Extending the model: Changes in modes of production Up to now we have worked under the assumption that we can represent the economy with an aggregate production function. However, this is not necessarily the only way to model the adjustment to the changes in the relative endowment of high-to-low-skilled labor. In particular, as Beaudry and Green (2003) suggest, if there are two modes of production, each of them characterized by different intensities of use of

[22]While for this to be true it is necessary that capital be not just a relative, but an absolute complement of skill – we need the response in (2) to be positive so that $\frac{\partial \ln K}{\partial \ln(H/L)} > 0$ – in this this three-factor setup capital is always an absolute q-complement of skill ($\partial^2 Y/\partial K \partial H > 0$) whenever it is a relative q-complement of skill (that is, whenever $\frac{\partial \ln(W_H/W_L)}{\partial \ln K} > 0$). As $H\frac{\partial^2 Y}{\partial K \partial H} + L\frac{\partial^2 Y}{\partial K \partial L} = -K\frac{\partial^2 Y}{\partial K^2} > 0$, the larger cross derivative must be positive.

the factors, then the economy can respond to the changes in the relative endowments choosing a different mode of production rather than just moving along the same isoquant as before.

To see how this works, consider the case where in the economy we can produce the same final good Y with two different modes of production: 1 and 2, and denote with by Y_i the amount of the good produced using mode i, and assume that for any set of factor prices mode 2 is low-skilled labor- and capital- intensive vis-a-vis mode 1, which is how Goldin and Katz (1998) model the difference between artisanal (mode 1) and industrial (mode 2) production, and that factor prices are determined in the economy. In this case, if we start from a high-skilled abundant situation and there is an increase in the supply of low-skilled labor, the new equilibrium will be characterized by a switching to mode 2. This final equilibrium will show a smaller effect on the relative wage of the low-skilled workers, and, more importantly, could be confused with a different level of complementarity between capital and both types of labor (in a single aggregate production function). In the context of the period where we have some new technologies being adopted, this is another mechanism we will explore by examining the response of indicators of production mode, such as plant size, to changes in skill mix.

Multiple Sectors A key value of the data we have digitized for this analysis is the ability to control for the potentially confounding influence of shifts in industry mix. Although so-called "Rybczynski effects" (endogenous industry mix adjustments) are generally found to be small in response to immigration-induced skill mix shocks (e.g., Card and Lewis, 2007; Gonzales and Ortega, 2011; Lewis, 2003), one recent study has found that changes in crop mix were the primary way in which the agriculture sector adjusted to immigrant inflows in the early twentieth century (Lafortune et al., 2013), at least on land which was suited to multiple types of crops.

The primary way in which we will address this is with industry controls (described in greater detail below). However, it is also possible to undertake a direct analysis of the importance of shifts in industry mix to the adjustment of local skill mix changes. We will ask whether sectors which are relatively more capital- or skill- intensive grow relatively more quickly with a relative influx of skilled labor.

3 Empirical Methodology

3.1 Baseline equation

Following the main results from our model, we want to estimate the following equation (for $J = N, Y$)

$$lnK/J_{cit} = \alpha_{early} \ln \left(\frac{H}{L}\right)_{ct} \times \mathbb{1}\left(t \in \{early\}\right) + \alpha_{late} \ln \left(\frac{H}{L}\right)_{ct} \times \mathbb{1}\left(t \in \{late\}\right) + \nu_c + \eta_t + \mu_{it} + \epsilon_{cit} \tag{8}$$

where K/J_{cit} corresponds to either the capital per worker or the capital-output ratio in industry i in county c at time t, $(H/L)_{ct}$ is the high-to-low-skilled labor ratio in the county c at time t, $\mathbb{1}\left(t \in \{early\}\right)$ and $\mathbb{1}\left(t \in \{late\}\right)$ are, respectively, indicators for the first and second half of our sample period (defined below), and ν_c, η_t, and μ_{it} represent country, time and industry-time fixed effects. All standard errors will be clustered at the geographical level and regressions are weighted as to give each geographical location the same weight.

Since our interest lies in comparing the evolution of the production function over our sample, we divide it between an early period and a late period, allowing α to change between the two. We unfortunately do not have sufficient variation to reliably estimate α separately by decade, though we can estimate it with as few as two decades. So what we do instead is move the cut-off points between an "early" and and "late" period to attempt to identify when, if any, changes seem to have occurred in the relationship we attempt to estimate. Since historical analyses by Chandler (1977) and Jerome (1934) argue that the Second Industrial Revolution transformed the productive process of manufacturing, we will look for a change around the 1880-1900 period, years during which some of the elements of the Second Industrial Revolution took place.

The interpretation of the coefficient α depends on the relevant outcome that is being estimated (as shown by the equations (3) and (4)). In equation (4), for example, where $ln(K/Y)$ is the outcome, it captures the complementarity between capital and skill relative to capital and low-skill: α will be positive if capital complements skilled labor relative to unskilled labor ($\alpha > 0$ implies that $\partial \ln(W_H/W_L)/\partial K > 0$).

Motivated in part by Goldin and Katz (1998)'s argument that capital-skill complementarity arises across sectors (in their model, across the combination of a machine- and goods-producing sectors), we also explore whether county- or city-wide (aggregate) outcomes are influenced by estimating the following equation, which corresponds to equation (8) but using data aggregated at the geographic level,

$$lnK/J_{ct} = \alpha_{early} \ln \left(\frac{H}{L} \right)_{ct} \times \mathbb{1} \left(t \in \{early\} \right) + \alpha_{late} \ln \left(\frac{H}{L} \right)_{ct} \times \mathbb{1} \left(t \in \{late\} \right) + \beta X_{ct} + \nu_c + \eta_t + \epsilon_{ct} \tag{9}$$

In this specification K/J_{ct} corresponds to the aggregate outcome variables from the previous estimation equation measured at the county level. Standard errors are again clustered at the county level and regressions are unweighted. In this case we can explore how the county as whole adjusts to the changes in the skill-mix of workers. Estimates of (9) may alternatively viewed as suffering from aggregation bias: shifts in output mix towards industries that use a different production technology could confound the results. This is why the industry-city data, which allow us to estimate (8) instead, are useful. The difference between Equations (8) and (9) would be driven by industrial composition shifts that occurred in response to changes in factor endowments. We will also test this directly by using as an outcome variable the share of labor, capital and output in industries that use some factors more intensively.

3.2 Identification strategy

Although our estimation equation and model are tightly linked, in practice identification is an issue: skill mix is likely to be endogenous, as workers' location (or skill acquisition) decisions are influenced by where their skills are most highly paid. Thus, depending on how our outcomes are correlated with relative wages, we could be over or under-estimating the through relationship between our variables of interest. Furthermore, it is important to note that manufacturing is only one sector in the broad economy – a minority of employment – so local demand shocks outside the manufacturing could be an important source of endogeneity.[23] It is thus difficult to sign exactly the bias of the basic correlations. OLS estimates might also be attenuated by error in the measurement of skill ratios due to sample variation.[24]

To solve these problem, we attempt to identify relative skill supply shocks using immigration-driven shocks to the relative endowment of high-to-low-skilled labor. As immigrants are themselves likely to elect locations based on economic conditions, we use in place of actual immigration the impact on skills, the impact that predicted inflows of immigrants, based on historical regional settlement patterns of immigration, would have on skill ratios. Specifically, the instru-

[23]According to the Census of Population, it ranges from roughly to one quarter to one third of employment in identified cities over the years in our sample, using industry codes constructed by Ruggles et al. (2010).

[24]We can get some sense of the magnitude of this using tabulated data on literacy rates by area (Minnesota Population Center, 2011), which are available for some (but not all) of the years in our sample. The comparison between our estimated literacy rates and the tabulated ones, conditional on the full set of fixed effects, suggests that OLS estimates might be 10-15% attenuated due to measurement error.

ment is given by:

$$\ln\widehat{(H/L)}_{ct} = ln\left(\frac{\sum_j \left(\frac{N_{jc0}}{N_{j0}}\right) HS\_jt}{\sum_j \left(\frac{N_{jc0}}{N_{j0}}\right) LS\_jt}\right) \tag{10}$$

where j represents each country or state of birth, c (US) county, and t period; N is the stock of immigrants/natives (not broken out by skill); HS_jt and LS_jt are the *national* stocks of high-skill and low-skill individuals from each country or state in each period t, respectively. Note that the numerator and denominator includes $\frac{N_{jc0}}{N_{j0}}$, which represents the share of individuals from j living in c in some base year. This is used to apportion the current stocks of immigrants by country and natives by state of birth to locations within the U.S. Thus, the instrument represents the ratio in the number of high- and low-skill individuals, respectively, that would be living in c if immigrants and natives were still apportioned across counties in the same manner as they were in the base year. This style of instrument has been widely used to study modern-day immigration impacts (see, for example Card, 2001; Cortes, 2008; Lewis, 2011) but until recently has seen limited application in this historical context. It attempts to circumvent the problem of endogenous location choice by allocating individuals to counties based on the location of immigrants from one's country of birth or one's state of birth in previous waves. We use the previous location of all immigrants instead of allowing high- and low-skilled individuals from a given country to be distributed in a distinct way such that these shares are less likely to capture economic conditions particularly suitable for a given skill level. Lafortune and Tessada (2013) provided significant evidence of ethnic network's role in the determination of the first location of immigrants arriving to the U.S., which supports the validity of the instrument. This contrasts a bit with Rosenbloom (2002)'s argument that labor markets were highly integrated by interregional (at least within the North) and even international migration (from Europe) by the late nineteenth century, although he also provides evidence that explicit international recruiting was a trivial component of factory hires (chapter 3). We return to this argument when we discuss the first stage: if true in the extreme, there would be no first stage relationship and our approach would not be feasible. As immigration patterns evolved over the entire period, we will use two base years: 1850 for 1860-1880 and 1880 for 1890-1940.

We modify the typical instrument by adding migration across states by natives as well. (10) including only immigrant groups in the index j does quite a good job of predicting immigrant skill ratios. However, we need something which predicts proportional total changes in skill ratios, so we need to normalize it by some defensibly exogenous measure of the skill ratio of natives in the area. The approach we settled on was to treat natives' state of origin as another set of "groups."[25]

[25] Another approach we tried was similar to Smith (2012)'s approach of obtaining the predicted skills of natives. We

The identification strategy has to fulfill the following two requirements to be valid. First, the total national stock of immigrant from a particular country at time t must not be correlated with differential shocks to manufacturing industries across counties. Given that few counties include a very large fraction of immigrants from a given country, it is difficult to imagine that the increase in the number of immigrants from a given skill group in a given country is driven by the higher demand for that skill in one or two counties. Second, the location choice made by immigrants in base years among counties should be uncorrelated with differential changes in the manufacturing innovations of the future. Namely, immigrants did not locate in cities where they anticipated that their skills was going to become more valuable in the future. We attenuate the concern regarding this second condition by using the stock of all immigrants (not only the ones of a given skill level) to predict the location of both skilled and unskilled workers in the future. This is preferred because the location choices of skilled versus unskilled workers in the base year may be more related to the anticipated changes in the manufacturing sector than the location choices of their aggregate.

Thus our instrument represents a predicted skill ratio based on the interaction of initial conditions and national changes in the skill and country-composition of workers. Because it is structured like the *actual* skill ratio, a first stage coefficient of one means that predicted immigration-driven changes in skill mix have a one-for-one impact on the actual skill ratio; coefficients different than one imply that the actual skill mix is offset by either native migratory response or other offsetting demographic changes (for example, if trends in native-born literacy differed in high- and low-immigration markets).

4 Data and Descriptive Statistics

Information regarding the number of high and low-skill individuals in a given locality can be obtained in each decade from IPUMS data (Ruggles et al., 2010) from 1860 to 1930 (except in 1890, where we use the 100% tabulations from the Census of population). There are really two options for defining "skill" in these data: occupation or literacy.[26] An advantage of literacy is that it is something close to a pre-labor market skill, whereas occupation-derived measures are a match between workers' skills and local labor market demand conditions. Furthermore, literacy is available uniformly during the period. It also correlates relatively well with the distinction of production and non-production workers where literacy would have been essential for the second type of employment but not for the first. Finally, it has also been documented that US

used the base year ratio of high- and low-skill natives interacted with the national growth rate of skills among native-born workers. Thus, this version of the instrument represented the predicted skill ratio given the initial locations of immigrants and natives and *national* changes in the country mix of immigrants and the skill mix of immigrants and natives. Similar results were obtained and are available upon request.

[26] Completed education is not available until 1940; only measures of school enrollment for youth are available prior to that time.

natives achieved higher rates of growth in literacy than sending countries, making immigration particularly important in determining the illiteracy of the US labor force.

Recall that we use predicted immigration as a shock to skill mix local labor markets that immigration generates over the period 1860 to 1930. This is a period of great potential for this purpose as immigration flows were very large. It also includes periods of slower immigration driven by potentially exogenous factors (Civil War, First World War) and by a dramatic change in the legal environment (1924's Johnson Act). We propose to use an instrumental variable approach as detailed above in equation (10). To construct this instrument, we require a reliable estimate of the location of immigrants of different origins in a "base year" (the $\frac{N_{jc0}}{N_{j0}}$ in (10)). Recall that we use two different base years, 1850 and 1880. For both we obtained a 100% samples. For 1850, the data came from the preliminary samples of the North Atlantic Population Project and by querying www.ancestry.com (for states not yet available); and for 1880, we used a 100% sample from IPUMS. We use these 100% tables to alleviate concerns of small-cell biases (see Aydemir and Borjas, 2010). We also need to obtain the national stock of immigrants from each country by country/state of birth and skill. In principle, are several ways we could have constructed the national number of high and low-skill immigrants arriving after 1850. To be as consistent as possible, chose to measure the with the stocks from each country (and U.S. state) in 1850 to 1930 by aggregating IPUMS data.[27]

Our outcome variables focus on the adjustment mechanisms in the manufacturing sector over this period. Our conceptual framework calls for data at the level of the labor market x industry. These can be obtained from published Manufacturing Census tabulations. Conveniently for our analysis, manufacturing censuses occurred roughly concurrently with the Census of Population over this entire period. Unfortunately, the tabulations are available only in paper format but we have digitalized them.[28]

One issue in covering such a long time series is that the unit of geography reported in these tables changes over time. We merged counties over time to ensure that borders were very similar between years. In 1860 and 1870, the data is available only available by county while in 1880 and later, the main geographic tabulations are for largest cities, occasionally supplemented by tabulations for selected urban counties. Because of this change of geography, and because, with rare exception, cities are within county boundaries, we have chosen to make "county" the unit

[27]From 1900-1930 we could have used the Census question regarding the year of entry; we chose not to use this because it is only available in these years. Another option was to use the flow by ethnicity and literacy available from the Report of the Immigration Commissioner of the period (from 1899-1932) and for some additional periods previous to that. Furthermore, immigrants include not just the net stock but the total flow which may be more exogenous than the number who eventually stay in the United States (Angrist, 2002). However, the fact that the data is, for some years, reported at the ethnicity level and for others at the level of the country of last residence, may introduce more noise in the variable, making the first stage weaker. Other alternatives such as the Ellis Island data set, which includes all passengers who arrived to the port of New York (Bandiera, Rasul and Viarengo, 2013), does not include any variable that would allow us to classify immigrants by their skill level.

[28]See Data Appendix for an exact description of all tables we entered for this project.

of analysis for our skill ratio measure, matching each city to the county they correspond to.[29]

In later years there is a minimum "cell size" to be included (often, at least 3 establishments) while in 1860 and 1870, it appears that almost all establishments were tabulated.[30] However, even with these reporting restrictions, there is "balancedness" in the sense that the industries detailed for each city often repeat, allowing us to use panel methods as detailed in the empirical methods section.[31]

While we obtained measures for a variety of outcomes, we here focus on capital, labor and output, which are the ingredients of our theoretical framework. Value of products and costs are available for the full period, which allows us to define value-added as our measure of output (Y). To measure labor (N), we use the measure of all workers. Value of capital, our key variable, is only available from 1860 to 1920. However, in 1910, 1920 and 1930, we have a measure of horsepower which we use to obtain a proxied measure of capital for 1930 based on the relationship between horsepower and capital in the two previous decades. Since this measure of capital includes all forms of capital (land, buildings, machinery and equipment), we may also wish to look at a measure that focuses a bit more directly on machines instead of land. We first propose to use horsepower directly. As we discussed before, this variable is available for 1910-1930. Before 1910, we use machinery and equipment since for 1890 and 1900, capital is decomposed into subcategories and we are able to obtain a measure of machinery and equipment capital directly. We merge these two series by transforming machinery and equipment into proxied horsepower from estimating at the state level the relationship between machinery and equipment and horsepower in 1900.[32] Before 1890, we were unable to obtain any similar measures but from the sample data of Atack and Bateman (1999), we were able to find evidence that very few firms had positive horsepower in 1860. We thus replace our measure of horsepower with 0.1 for 1860 for all industries and counties.[33]. Finally, capital utilization may also respond to skill ratios so we use expenditure on fuel and rent of power (in some years it is a single category while in others, it was decomposed) as an alternative measure of capital which may capture more utilization than purchase of capital. Again, since that variable is only available from 1890 onwards, we used micro-data from Atack and Bateman (1999) to determine that few firms devoted large amounts to fuel and power in 1860 and we thus proxy it with 0.1 for all industries and counties in that

[29] The only significant exception to this is New York City, which spans multiple counties and whose county composition changes over time. We therefore construct New York City to cover the five "boroughs" (counties) that make it up at the end of the period throughout the entire 1860-1930 period. This aggregates together Brooklyn and New York City, which reported as separate cities in earlier years.

[30] Home industries, which may have been important in these early years, were not included; there was also a sales threshold for inclusion.

[31] Industries were matched by hand by the authors, aggregating where necessary to create consistency over time. Census reports were used from 1900 onwards where merging and disaggregation were detailed. For periods previous to that, some comparative tables were used as a guide. Details are provided in the Data Appendix.

[32] The estimated relationship suggests that Horsepower=0.004*M&E Capital.

[33] Including this does little to alter the results of our "late" period but does allow us to estimate a parameter for the "early" period which is why we chose to make this assumption.

year.

Only from 1890 onwards, we can also distinguish between wage earners and salaried officials, something that we will use to proxy for production and non-production workers when we need to do so as in Goldin and Katz (1998). We also have access to the total wage-bill which we can divide between the share accruing to each type of workers starting in 1890. We further complement this by estimating, in aggregate, the fraction of production and non-production workers that were literate and illiterate using the occupation reported in IPUMS. We use this to estimate $\phi_H = 0.85$, the fraction of workers in manufacturing that were literate. We also estimate W_L and W_H (and thus s_L and s_H) by allocating the wage-bill of each worker type (production/nonproduction) to literate and illiterate workers according to their representation in each type. This is definitely a lower-bound estimate of W_H and s_H since it assumes no return to skill within production or non-production workers. We obtain estimates of $s_L = 0.0787$ and $s_H = 0.5085$, implying that the capital share was around 40 percent, consistent with Taylor and Williamson (1997).

We restrict our sample of analysis to any county for which a city was included in the Census of Manufactures over this period for at least 3 distinct occasions. In the aggregate analysis, we include all industries for a given city/county. In the industry by area analysis, we exclude the residual "All other industries" cells, as they are not comparable across years or areas and also exclude industry-year cells where the industry was appeared in no more than 2 areas in that year.[34] Merged all together, we obtain a very rich panel including 37,278 industry-city-year observations. This includes a total 175 areas (more in some years than in others) and 137 industries (our classification over time generated 150 separate industries but 13 of them were eliminated due to the fact that they had too few observations in a given year). These area cover on average 58 percent of the U.S. immigrant population, and the industry division is very detailed.

The means of our sample are shown in Table 1 in which we present the three different distinctions we will make between early and late period. In the first panel, we call "early" 1860-1880 and the rest as late. In the second panel, we move our window by 10 years, implying that all observations from the 19th century are called "early". Finally, the last panel includes only 1910-1930 as "late" observations. What we can observe is that there is capital deepening over the full period, as can be seen from the change in values as we alter the cut-off points. Literacy in the US was also relatively high over this period with the logarithm of skilled per unskilled worker of around 2 in the 19th century and growing to about 3 in the early 20th century (implying a change from about 80 percent of the workers being literate to almost everybody being literate by 1930). Our predicted measure seems to be slightly lower than the actual one, suggesting that endogenous migration exacerbated existing differences.

[34] The latter is essential to the construction of our standard errors.

5 Results

5.1 First stage

Our identification strategy relies on the impact regional clustering of immigrants has on skill ratios as the origin composition of immigrants shifts over time, an approach which seen a lot of use in modern studies of the labor market impact of immigration. While far from unchallengeable as a source of exogenous variation, it is demanding instrument for a number of reasons. First, we are allocating immigrants (both high and low-skill) using the county of residence of *all* previous residents, no matter what their skill or occupation. If there is any correlation between occupations and location (as shown in Lafortune and Tessada, 2013), this is more likely to be exogenous but also costly in terms of power. Second, we allocate immigrants arriving over using fixed location shares. This requires a fair amount of stability in the location choice of immigrants. Finally, this instrument also relies on the skill mix of immigrants of different origins differing substantially.

Before turning to the first stage results, it is worth considering in more specific detail the components of variation in the instrument over this period. A primary source is the differences in the distribution of immigrant groups across locations, (the $\frac{N_{jc0}}{N_{j0}}$ in (10)). In other words, where were the enclaves? For the 1850 base year, which we apply to the nineteenth century data, the top locations of the six largest immigrant groups are shown in Data Appendix Table 1. Although New York is the top locations for all groups (or close to it for Canadians), and port cities are common for all groups, the pattern of destinations other than New York tends to differ across groups. Note that Italians and Russians had already begun to cluster in San Francisco long before the big wave of Italian and Russian migration.

A second sources of variation in the instrument is that in the country composition of immigrants over time, shown in Figure 1 for the same six groups. Irish immigration peaks early in the period, German in the middle, and Italian and Russian/Polish immigration latest. A third source of variation is the skills of the different immigrant groups compared to the native-born population. That will depend on the particular market under study, but this Figure 2 shows it in the aggregate.

Figure 2 shows the conventional wisdom: German and English immigrants were high skill, so concentrations of them would tend to raise the average skills of workers in an area. In contrast, by the time of the wave of Russian and Italian immigration, these groups had very low literacy skills compared to the native-born population. A full list of the origin groups used in the construction of the instrument, and the data underlying Figures 1 and 2 (for selected years) are shown in Data Appendix Table 2.

Table B.1 in the appendix shows the first stage regressions estimated in the industry x county level data combining all years of data. To both account for the fact there are multiple "copies" of

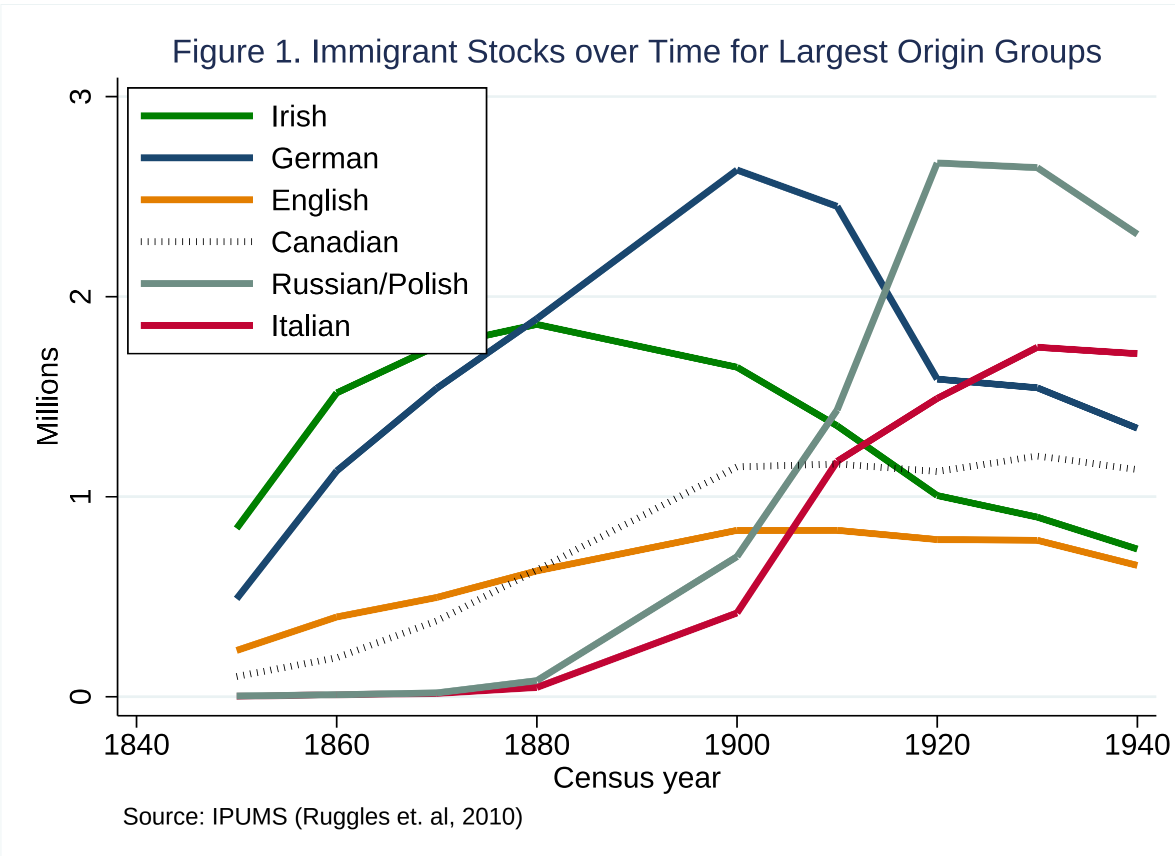
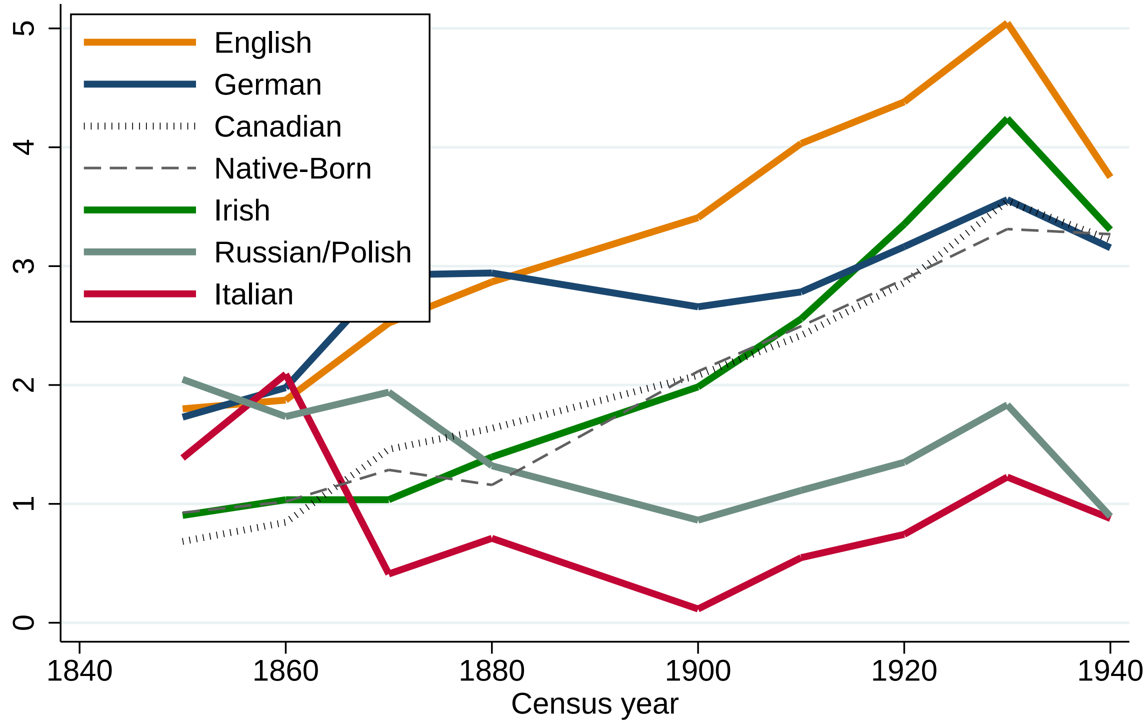


Figure 1. Immigrant Stocks over Time for Largest Origin Groups
Irish
German
English
Canadian
Russian/Polish
Italian
Millions
0
1
2
3
1840
1860
1880
1900
1920
1940
Census year
Source: IPUMS (Ruggles et. al, 2010)

Figure 2. Ln(High/Low Skill) over time for Largest Origin Groups



Source: IPUMS (Ruggles et. al, 2010). High Skill=Literate.

county within a year and for the fact that the errors are likely autocorrelated over time, we cluster standard errors by county. In addition, we weight by the inverse of the number of industries represented in a county (to give each county equal weight).[35] As we move from Column (1) to (3), we explore increasingly demanding controls for industry, which will parallel our analysis below: with no industry effects, with industry effects, and with industry x year effects. In Table B.1, the only reason they should make any difference is because of small changes in the composition of areas which identify the relationship (since the instrument and skill mix measure do not vary by industry). The results suggest that these added controls change little the first stage which remains very highly significant and almost unmoved in terms of magnitude. The results suggest that a change in 1 percent in our predict skill ratio translates into about a 0.75 percent change in the actual skill ratio of a county. This could be consistent with endogenous location choice by natives and immigrants, some deterioration of the settlement patterns from historical patterns, or both.

Recall that our skill ratio will be interacted with a period-indicator for "early" or "late". Thus, we will not only have one first stage but two first stages for each of these interactions. However, Wooldridge (1997) suggests that it is more efficient not to interact the instrument with such an

[35]The standard errors are larger if we do not make this weighting adjustment, but the F-stat remains above 10.

indicator variable but instead to use the first stage we presented in Table 2, obtain the predicted values and interact them with our indicator dummies. We do this and obtain a very strong first stage for each sub-period of analysis. Nicely, skill mix tends to load onto skill mix from the appropriate period, and the confidence interval usually includes one.

5.2 Responses of capital

Having shown that our instrument is capable of generating significant variation in the endogenous variable, we now turn to exploring how capital responded to the change in the skill ratio generated by immigration. Table 3 shows results at the "aggregate" level, that is using only variation across areas, not accounting for potential differences in industry mix. Columns (1) and (3) examine capital per worker and columns (2) and (4) capital per dollar of output. The first two columns present the OLS while the last two show the IV estimates. OLS seems to show limited responses of capital ratios to change in skill ratios. The estimates are only significant in one case and relatively small. The IV estimates, on the other hand, suggest that capital per worker positively responded to an immigration-induced increase in skill ratios in both our "early" and "late" periods. Except when we divide the sample by century (1860-90/1900-1930), the two estimates are also very similar in magnitude. The capital-output ratio, on the other hand, is consistently negative but rarely significant. The estimates for the late and early period again seem to be relatively similar, except when we divide the sample by century. From these aggregate results, we would thus conclude that capital-skill complementarity appear to have arisen at the beginning of our sample but that low-skill workers were also q-complements to capital for the capital-output ratio to be slightly negative.

A concern with results in Table 3 is that they are potentially driven by shifts in industry mix: that is, more less skilled workers may attract less capital intensive industries (e.g., Goldin and Katz, 1998; James and Skinner, 1985). To address this, we now turn to estimates that allow us to examine *within* industry responses to aggregate skill mix changes, using our data on production techniques detailed by area and industry. In the next section, we will also examine the response of industry mix directly, and how much of our results it can account for.

Table 4 shows ordinary least squares (OLS), and Table 5 shows instrumental variables (IV) estimates of the relationship between skill mix and capital measures at the industry x area level. The first 3 columns of each table focus on the capital per worker while the last 3 columns present the results for the capital-output ratios. The panels are organized as previously depending on the moment in which our sample is split between "early" and "late" periods. For each outcome and period, we successively increase the number of fixed effects, starting from none, to fixed effects for industries and finally for industry-year fixed effects.

We first consider the results of the OLS regressions in Table 4. We find that the results are fairly similar to those of the aggregate regressions, although much more often significant than previously. We find that an increase in skill mix is positively associated with capital per worker measure throughout the period but increasingly so as the difference between the late and early period are particularly salient once 1910-1930 are the only years included as “late”. Capital per output is also positively associated with an increase in the skill ratio but less so than for capital per worker. Nevertheless, we see also in this case that by the time we contrast post-1900 to previous years, there is a stronger positive association in the twentieth century than before.

Let us now consider the IV estimates in Table 5. In that case, we tend to observe a negative impact of skill ratio on capital per worker in the early period for the first two cut-offs and a positive coefficient for the late period. The results are only statistically significant when we exclude industry fixed-effects. Once they are added, the coefficients become less large and also less significant. From the model, this suggests that capital-skill complementarity used to be much weaker in the “early” period than in the late period. In particular given the values of the coefficients in the “late” period when that period only includes 20th century values, we would even obtain some indications that capital would have become q-substitutes with low skill labor at that time.

We then turn to the results regarding capital-output ratios. We find that as the skill ratio rose, capital-output ratios fell in the “early” period and sometimes increased in the “late” period, in particular as our sample is split in later years. The results are only significant for when our sample is split across centuries (1860-90/1900-1930). Using our framework, this would imply that in the early period, capital was relatively more complementary with low- than high-skill workers, but its relative complementary with low-skilled workers fell (and its relative complementarity with skilled labor increased) as time passed. As we will discover below, the magnitudes of the positive coefficient in the “late” period may even suggest that capital and low-skill workers became q-substitutes.

Thus, while the statistical significance of our results is weaker than one would hope, the magnitudes are clearly suggestive of a change in the relationship of capital with skilled and unskilled labor as time went by. This is consistent with what some historians have previously argued, that in the nineteenth century capital was a relative substitute of skilled labor, and became a relative complement of skilled labor only some time later in the nineteenth or early twentieth century.[36] The argument is that early factories were low-skill and capital-intensive relative to the alternative, artisanal production. In light of this, it is interesting that we do not find a significant association between skill supplies and establishment size in the early period (B.2).[37] While not

[36]Note from the theory this implies that immigration-driven increases in skill ratios in the early period would have reduced wage gaps for two reasons: because of the direct effect on skill prices through supply, and the reduction in capital intensity would have had an additional impact. This contrasts with the more recent period, where the adjustment of capital partially undoes the impact of immigration on relative wages. We further discuss relative wage impacts below.

[37]This contrasts with Kim (2007), who find an association between immigration, not parameterized by skill, and

entirely ruling out that capital's response is due to a shift between "modes" of production, this is not consistent with the being driven by shift between artisanal and factory production. Another way to see it as providing reassurance that results are really being driven by changes in production technique, as, for example, Katz and Margo (2013) argue establishment size can significantly confound estimates of the changes in capital usage.

OLS estimates would have not been able to tell us this as they implied that capital-skill complementary was present since the beginning although maybe increasing over time. A standard story would be that OLS estimates are attenuated by measurement error. This seems a plausible contributor to bias in this context, with a crude self-reported measure of skill conditional on a large number of fixed effects. However, there seems to be alternative sources of biases because the estimates do not simply appear to be biased towards 0. A key unobservable might be the local outside (non-manufacturing) option of low-skill workers. For instance, to take a Goldin and Sokoloff (1984) type of story, certain areas may have very productive agricultural land. In such areas, low-skill workers might drawn to the area but away from manufacturing, which could reduce the adoption of capital- and low skill-intensive production techniques.

One may be worried that our measure of the value of capital may not be as close as to what we wish to measure since it includes land and buildings. We thus turn to our two alternative measures of capital, namely horsepower (which in some years is predicted from value of machinery and equipment) and fuel expenditures and rent of power. These two measures are only available from 1890 on but we extrapolated their value for 1860 as well. However, since our instrument requires at least 2 years within each sub-period, this implies that we cannot get an estimate of the causal effect of a change in the skill ratio when the early period only includes 1860-1880. Thus, Table 6 includes only two panels instead of three for that reason. The format of the table mirrors that of the previous one except that for each outcome, we now have two different measures. Columns (1)-(3) and (7)-(9) measure capital from fuel expenditure and the others from horsepower and its proxy. A difference to keep in mind between this table and the previous one is that we have limited information in the "early" period thus limiting our capacity to make comparisons. This may explain why in this table, we do not estimate a negative coefficient as we found previously for the "early" period. For fuel expenditures, we see a very clear pattern emerging, nevertheless. When we split the sample by century, we find clear indication that capital and skill were much more complementary in the late period than in the early one. However, once we include 1900 into the early period, we find coefficients that are much more similar, suggesting that the shift in the complementarity between inputs may have occurred around the end of the nineteenth century. The results for fuel expenditures are relatively robust to the inclusion of fixed effects. The conclusions for horsepower are similar but less robust to the inclusion of fixed effects for industry or industry-year.

plant size.

If we use our theoretical framework, we would deduct the results of capital-per-worker that fuel expenditure has always been q-complement with high-skill workers but that this increased strongly around the turn of the twentieth century. Horsepower would have been q-substitutes with high-skill workers and this would have flipped as the Second Industrial Revolution evolved. Capital-output ratios would tell a story of a changing relationship for both type of proxies for capital.

Conducting our analysis separately may be penalizing us since we are estimating the same fundamental relationship using two different capital-ratios. If we assume that our framework is correct, then we can combine the two equations to potentially improve the precisions of our estimates. One can note from our theoretical framework that

$$\frac{\partial ln(K/N)}{\partial ln(H/L)} = -\phi\kappa + (1-\phi)(1-\kappa) = 1-\phi-\kappa$$

$$\frac{\partial ln(K/Y)}{\partial ln(H/L)} = s_L(1-\kappa) - s_H\kappa = s_L - (s_L+s_H)\kappa$$

where

$$\kappa = \frac{L\frac{\partial^2 Y}{\partial K \partial L}}{H\frac{\partial^2 Y}{\partial K\partial H} + L\frac{\partial^2 Y}{\partial K\partial L}}$$

This system is over-identified as there are two equations and one unknown parameter, which is κ. Formally, we can estimate a system of two equations given by:

$$\ln(K/N) - (1-\phi)\ln(H/L) = \beta(-\ln(H/L))$$

$$ln(K/Y) - s_L \ln(H/L) = \beta(-(s_L+s_H)\ln(H/L))$$

and impose that the coefficients β, which is an estimate of κ be identical in both equations.

κ measures absolute q-complementarity between capital and skills. To interpret it, recall from (5), that $\frac{\partial ln(K/Y)}{\partial ln(H/L)} > 0$ defines what is often called capital-skill complementarity (e.g., Goldin and Katz, 1998; Krusell, Ohanian, Rios-Rull and Violante., 2000), a condition under which capital proportionately raises the marginal product of skilled labor more than unskilled. From above, the two are related by $s_L - (s_L+s_H)\kappa > 0$, or $\kappa < \frac{s_L}{s_L+s_H}$. Thus, this joint estimation of κ allows us to draw simple conclusions about the relationship between inputs:

- If $\kappa > 1$, then capital and skills are q-substitutes and capital and low-skill are q-complements
- If $1 > \kappa > \frac{s_L}{s_L+s_H}$, then capital and both types of labor are q-complements with capital but capital is more complementary to low-skill labor than high-skill labor

- If $\frac{s_L}{s_L+s_H} > \kappa > 0$, then capital and both types of labor are q-complements with capital but capital is more complementary to high-skill labor than low-skill labor
- If $\kappa < 0$, then capital and high-skill labor are q-complements and capital and low-skill labor are q-substitutes

Recall in section 4 we calculated that $s_L = 0.0787$ and $s_H = 0.5085$, which produces a cutoff of about $\frac{s_L}{s_L+s_H} = 0.135$. We perform this estimation and report the results in Table 7 where we report a different estimate of κ for early and late periods using three different cut-offs in each panel, as before. The first three columns use our regressions of the value of capital, the next three our fuel expenditures and the last three, our horsepower measure. For each of these outcomes, we also explore what is the impact of increasing the number of fixed effects employed in the regressions.

We can see that we do gain some statistical power by imposing some structure on our estimates. We can now argue that there was q-complementarity between capital and low-skill labor in the early period when using the value of capital as our measure of K. This is statistically significantly different from 0 in a number of cases but appears to be decreasing in magnitude and weakening in terms of statistical significance as we move our time window such that the early period includes later and later decades. By the "late" period, we cannot reject that κ is equal to zero but it is, in almost all cases, negative, indicating that capital and low-skill would have become less and less complementary over time, leading to larger and larger complementarity between high-skill and capital. When we use fuel expenditures, we find an estimate of κ that is clearly negative in the late period and statistically significantly different from 0. When we divide the periods by century, the early period shows a number that is not robustly statistically significant and smaller in magnitude than in the late period. This switches when we include 1900 in the early period, suggesting that right around the turn of the century, capital and skill became stronger complements than they were previously. For horsepower, we see a very similar pattern when we do not include fixed effects by industry but these are not robust to the inclusion of additional controls.

Overall, these "structural" results suggest that capital and high-skill labor (as measured by literacy) have been consistently complementary in manufacturing since at least the 1860 but that this relationship was strengthened substantially around 1890-1900 when, in some of our estimates, it became so complementary that low-skill workers became substitutes for capital. This also seems to vary by type of capital where technologies using fuel and horsepower appear to have been more complementary with high-skill workers than other types of capital. Furthermore, we have explored how sensitive our results are to our assumptions and have found little reason to believe that the results we present would look different if we had used the estimates of parameters for any other years.[38].

5.3 Adjustments of Industry Mix

Our estimates were, in some cases, sensitive to industry mix controls So we now directly explore whether the change in skill availability within an area altered the industry mix. The difference between our aggregate results and our industry-level results may indicate that there is some change by industry mix but it is difficult to quantify it. We present, in Table 8, the IV estimates of a regression of the share of low-skill workers employed in each quartile of the distribution of firms on the skill ratio in the area. Since these regressions are run by area and not by industry, they only include area and year fixed effects as those in Table 3. To measure industry shift, we need to divide our industries in categories as running the share of each industry separately would be too lengthy and difficult to interpret. As a first approximation, we separated industries based on their capital/labor and non-production/production workers ratios at the national level in the first year that variable was provided in the data (namely 1860 for K/N and 1890 for H/L).[39]. We find some evidence that the change in factor availability at the local level also impacted industry composition but only for the division of firms by their non-production/production workers ratio. We find absolutely no evidence that the change in factor ratio significantly impacted the share of production workers hired by each industry. However, we do find some evidence that industries in the second quantile in terms of non-production workers/production workers did expand significantly in response to a higher skill ratio.

Combining these with the difference in factor intensity of each industry, we find very limited evidence overall that these shifts allowed the economy to absorb the area-level shift in skills availability. What we do here is we multiply the response in terms of size of industry by the factor-ratio in each of these quantiles and sum them up. By dividing that sum by the average factor ratio in the economy, we then obtain what is the change in percent that would have been generated through shifts of industries alone. We find that shifts in industry mix would have led to a decrease in the capital intensity. That decrease would have been of about 9 percent when using 1860-1880 and 4 percent in 1890-1930. For our second panel, in both periods, the change in industry composition would have decreased the capital/labor ratio by about 6 percent. Finally, in our last panel, the shifts in industry composition would have led to a 6.5 percent fall in the capital-labor ratio between 1860-1900 and to a small increase of 1 percent in the 1910-1930 period. These are simply averages and given the fact that none of the coefficients are significant, should not be perceived as in any way precise. Nevertheless, they suggest little role for the pattern we observe in aggregate to be driven by shifts across industries. The results for the skill ratio are

[38] Results not presented but available upon request

[39] We also used the average value for all years where the information was available with very similar results, available upon request

all negative and extremely small, suggesting even less of a role when measured in this fashion. Furthermore, we do not see much evidence of a change as time goes by suggesting that we cannot justify the pattern we identify as time passes.

Overall, these results seem to suggest little role for within-manufacturing sectoral reallocations in response to the skill shock. Finally, while not reported here, we also find that areas which experienced an increase in their skill ratio over the later period did observe a lower growth in manufacturing employment than other areas.[40] The coefficient for the earlier period is positive and not significant.

5.4 Relative Wages

Given that we are finding adjustments of production technique within industry in response to skill mix shocks, we turn to an examination of wages: a producer's adjustment of capital intensity in response to shifts in skill ratios theoretically comes through the signal of relative factor *prices*. A fall in low-skill relative wages due to low-skill immigration induces producers to adopt more capital-intensive techniques, say, in our early period. Measuring this signal directly is challenging, however, as individual-level wage data are not available until 1940 in IPUMS. Furthermore, the only available data we have from the Census of Manufacturing is, as we detailed previously, wages by production/non-production workers and only starting in 1890. Thus, we are here unable to do any analysis shifting our periods as we can at best identify an early period by combining 1890 and 1900 and a late period including the rest.

Starting in 1890, the Census of Manufactures asked separately about wages paid to "salaried officials" and "wage workers," which we use to construct a crude relative wage proxy as described above. Namely, we assume that all workers within a same category earn the same average wage and obtain a measure of the wage of literate versus non-literate individuals by assigning this according to the share of individuals in that year in IPUMS which report working as a production/non-production worker by their literacy status. The results using this measure are shown in Table 9. None of the IV estimates are significant and they are small and positive in almost all cases. This may be because of approximation of the wage ratio is just too crude. In particular, our estimates may be confounded by compositional changes in who makes up salaried officials and wage workers as literacy rates change.

6 Parametric Specifications, Calibration and Simulation

Having estimated that the relationship between capital and skill has strongly changed over our period of study and being limited by data to study directly the wage effects of the policies, we

[40] Results available upon request.

now take a more parametric specification to explore how this changing relationship may have affected how the US economy was able to absorb changes in skill mix generated by migration.

6.1 Setup

In order to simulate the wage and capital accumulation impacts of immigration, we turn to a parametric form for our single-good model of production in section 2. Capital-skill complementarity is generally modeled using a nested CES structure, which can either group together capital and skilled labor (e.g., Goldin and Katz, 1998; Krusell et al., 2000), or capital and unskilled labor (e.g., Autor et al., 2003; Lewis, 2011) in the inner nest. For example, the general form of the production function used in Goldin and Katz (1998) is

$$Y = A\left(\alpha(\beta K^{\theta} + (1-\beta)H^{\theta})^{\rho/\theta} + (1-\alpha)L^{\rho}\right)^{1/\rho}, \tag{11}$$

where $\rho > \theta$ implies capital is more complementary with high- than low-skill labor (and $\rho < \theta$ implies the). Goldin and Katz (1998) model the shift between different manufacturing production technologies – from hand production, to factory and assembly line and later to continuous and batch processes – as shifts in the parameters A, α, and β over time. Alternatively, Lewis (2013) runs simulations using the function

$$Y = A\left(\alpha(\beta K^{\theta} + (1-\beta)L^{\theta})^{\rho/\theta} + (1-\alpha)H^{\rho}\right)^{1/\rho}. \tag{12}$$

The only difference from (11) is the position of H and L in the function. In (12) instead $\theta > \rho$ implies relative capital-skill complementarity. Since there is not consensus on the "right" way to nest the production function, we will try it both ways, and see which fits the data better. Under (11):

$$\kappa = \frac{(1-\rho)s_L(1-s_L)}{(1-\rho)s_L(1-s_L-s_H) + (1-\theta)s_H} \tag{13}$$

while under (12)

$$\kappa = \frac{-(1-\rho)s_L s_H + (1-\theta)s_L}{(1-\rho)s_H(1-s_L-s_H) + (1-\theta)s_L} \tag{14}$$

On top of this, we can show that the wage impact will depend on κ such that

$$\frac{d\ln(W_H/W_L)}{d\ln(H/L)} = \rho - 1 + \frac{(\rho-\theta)(1-s_L-s_H)(-\kappa)}{1-s_L} \quad (15)$$

under (11) and

$$\frac{d\ln(W_H/W_L)}{d\ln(H/L)} = \rho - 1 + \frac{(\theta-\rho)(1-s_L-s_H)(1-\kappa)}{1-s_H}. \quad (16)$$

under (12).

Again, when capital is more complementary to skills the second term is positive. So like in section 2, the magnitude of the relative wage response to changes in skill mix is smaller than predicted by the short-run inverse elasticity of substitution (that is, $\rho - 1 < 0$). The appendix provides all the demonstration of the above equations.

6.2 Parameter Values

To estimate the impact on wages, we must first estimate (13) and (14). We have estimates of s_L and s_H described earlier (in section 4) as well as κ for different periods of our data but we do not have parameter estimates of ρ or θ. Obtaining estimates of ρ is especially problematic due to a lack of disaggregated wage data, which means we do not have good, direct estimates of (15) and (16). To deal with this, we will assume different values of the parameter ρ, where note that $(1-\rho)^{-1}$ represents the short-run elasticity of substitution between high and low-skill labor (and, as a check, we will compare our simulations to estimates in Goldin (1994) below). We will then set θ to be consistent with our estimates of (13) and (14), subject to assumed values of capital and skilled labor's share.

To see this, Table 10 maps out the parameter estimates and impact of a one unit change in $\ln(H/L)$ implied by various assumed parameter estimates, using, alternatively, model (12) (in columns 4-5) or model (11).[41] The top panel assumes, as Goldin and Katz (1998) did, that the outer nest is Cobb-Douglas ($\rho = 0$). As a benchmark, we will start by assuming that capital is not more or less complementary to skill, i.e. is "skill neutral," by setting $\theta = \rho = 0$, shown in row 1. This implies that relative wages fall one-for-one as skill ratios rise. (More generally, the relative wage impact of a one unit increase in $ln(H/L)$ is given by $\rho - 1$ in the skill neutral case $\theta = \rho$ – see (15) and (16).)

Next, let us turn to choosing parameters consistent with our estimate of κ for 1860-80 of 0.3, shown in row 2 of the table. This implies a negative value of $\theta = -0.85$ when capital is nested with unskilled labor and a positive value of $\theta = 0.58$ when capital is nested with skilled labor. In

[41] This is generalized from a similar table in Lewis (2013).

both cases, this implies that capital is q-complementary with both skilled and unskilled labor but more so with skilled than unskilled labor. In the capital-unskilled nesting, wage impacts that are *larger* than the capital neutral benchmark in row (1), as capital adjustments magnify the relative productivity impact of changes in skill supply. This does not happen here when capital is nested with skilled labor.

In contrast, as noted in 2, if the response of capital output ratios to skill mix is positive (and so κ is negative) – so that capital and skill are relative complements – then the relative wage impacts are smaller than the benchmark case. When capital nests with unskilled labor our estimate of $\kappa = -0.1$ for 1890-1930 from Table 7 implies the impossible $\theta > 1$, which casts some doubt on the appropriateness of this nesting. However, when we nest capital with unskilled labor, we obtain a large positive estimate of θ that is in the admissible range below one. In that case, the impact of the change in skill ratio on the relative wage is strongly attenuated by the response of capital, with magnitudes about one third that of the "skill-neutral" benchmark case in the table's first row. Interestingly in modern data and using a similar approach, Lewis (2011) estimates a κ only slightly more negative (albeit for different skill categories, high school dropouts and completers) than the one we obtain for the "late period," potentially consistent with Goldin and Katz (1998)'s story about modern capital-skill complementarity being a continuation of similar relationship between labor and non-labor inputs in this earlier era.

Using the Lewis (2011) estimates instead implies an even smaller relative wage impact (row 4 of the Table). The few estimates of κ in Table 7 that are even more negative would thus imply even smaller wage impacts. This is taken to another extreme benchmark that was discussed in section 2, the case from Autor et al. (2003) in which capital and low-skill labor are perfect substitutes. In this case, changes in skill ratios have zero impact on relative wages.

How sensitive are these relationships to different parameter choices? The pattern of relative magnitudes are not sensitive to the choice of our least well justified parameter ρ, the one which governs the elasticity of substitution between skill types. For example, the bottom panel shows the same set of simulations with instead ρ set at 0.33, which is roughly what you would need to get to the consensus value for the elasticity of substitution between college and non-college labor in the modern U.S. labor market (e.g., Hamermesh, 1993). The absolute wage impacts are smaller in this panel (by design of the larger elasticity), but the proportional difference across rows varies in nearly the same way as the upper panel (for example, the estimates in row 8 are about one-third those of row 6). The same pattern emerges consistently for other values of ρ (not shown in table).

Interestingly, the estimates in the lower panel of Table 10 are also roughly in line with the reduced form elasticity of substitution between artisans and laborers implied by estimates in Goldin (1994), whose estimates come from the middle of our period of study.[42] Given the large

[42]Goldin (1994) combines wage data by broad occupation in several cities from 1890-1907 with percent foreign born

differences in methodology, perhaps not too much should be made of this; nevertheless, because of this similarity, the estimates in the lower panel will be used to simulate the impact of counterfactual immigration flows in the next section.

The estimates of s_H and s_L we have been using were calculated from aggregate data assuming that within occupational groups, there are no "return" to literacy, that is, within each of production and non-production status that each worker received the same wage. In fact, to the best of our ability to measure it, the "return" to literacy, that is $ln(w_H/w_L)$ may have been around 50% over most of the years of our sample. We estimated this using the Iowa Census (Goldin and Katz, 2010), which has actual data on earnings, and in the U.S. Censuses of Population (Ruggles et al., 2010), using 1950 "occupation score" (that is, the mean wages in the person's reported occupation in the 1950 census). We limited to the sample to urban native-born who are at least age 20.[43] Figure A1 shows our estimates of the return to literacy by year.[44]

We are using that $\phi_H = 0.85$ and $ln(w_H/w_L) = 0.5$, which means that that $H/L = 5.7$ and that the relative wage bills $\frac{H}{L}\frac{w_H}{w_L} = e^{0.5} * 5.7 = 9.34$. Given this, we could think that estimates of s_H and s_L that would be potentially more realistic would be $s_H = 0.53$ and $s_L = 0.06$, which is not that different than what we are using. The results for our estimates of κ are robust to these changes; if anything, sensitivity of wage responses to the level of κ are even more marked than is shown in Table 10 with these alternative share parameters.

6.3 Simulating the Impact of Immigration

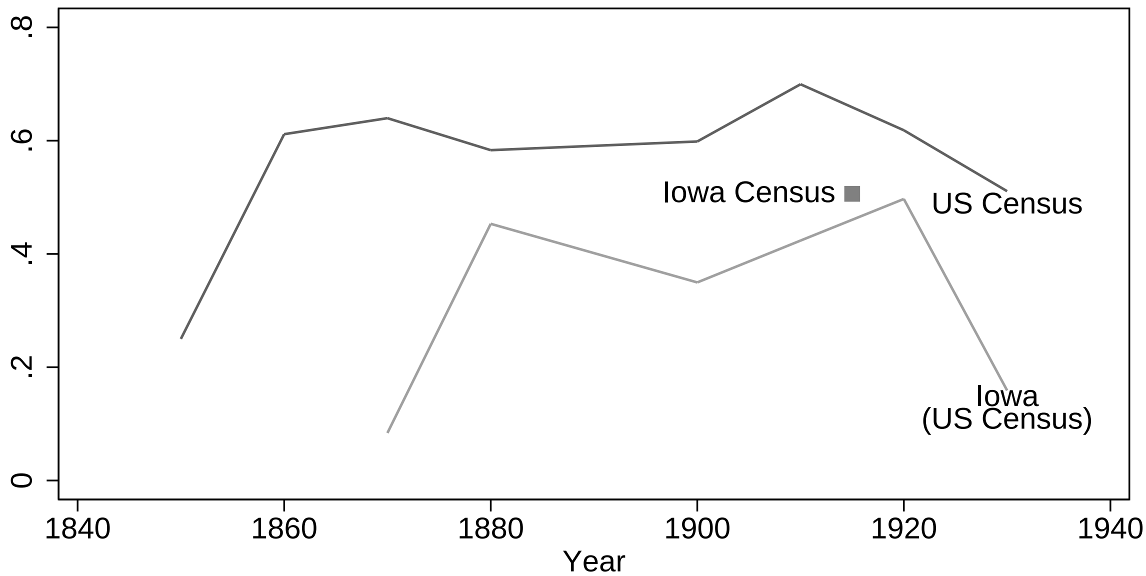
The one unit increase in $ln(H/L)$ used in the Table 10 simulations may not be typical of the impact of immigration. So now we turn to simulations based on the actual experience of the U.S. economy with immigration during the period of our estimates. Table 11 shows estimates of the impact of immigration on wage ratios in manufacturing under various counterfactual immigration scenarios, using the estimated capital responses from the period under study to

estimated from the Census of Population to estimate the regression $\Delta \ln w_{oc} = a + b_o \Delta F_c + \mu_c$, where $\Delta \ln w_{oc}$ is the ln change in the wage in occupation o and city c and ΔF_c is the change in the share foreign-born in the city. Her estimates tend to be more negative for laborers than artisans, consistent with a relative wage impact of an increase in the relative supply of less-skilled labor induced by immigration. To convert her estimates to a reduced-form relative wage impact of the sort shown in columns (5) and (7), we use the fact that $\frac{d\ln(W_H/W_L)}{d\ln(H/L)} = \left(\frac{d\ln W_H}{dF} - \frac{d\ln W_L}{dF}\right)\left(\frac{d\ln(H/L)}{dp}\frac{dp}{dF}\right)^{-1} \approx (b_{artisans} - b_{laborers})[p(1-p)]/(p_F - p_D)$, where $b_{artisans} - b_{laborers}$ represents Goldin's slope estimates for artisans relative to laborers, $p = \frac{H}{H+L}$ represents the share "skilled" (artisan), and p_F, and p_D represent the share skilled for foreigners and domestic workers, respectively. In the upper panel of Goldin (1994)'s table 7.8, $b_{artisans} - b_{laborers}$ ranges from 0.481 to 1.465 depending on time period. (Caveats: each of $b_{artisans}$ and $b_{laborers}$ was estimated in a different sample of cities; the estimates are also possibly confounded by the direct compositional impacts of immigration.) If p is 0.9 (the non-laborer share in manufacturing and construction in 1900) and $p_F - p_D$ is about -0.2 (the gap in this share between immigrants who arrived in the 1890s and natives) then the reduced form relative wage impact will be in the range of -.66 to -0.22, which overlaps with the wage impacts in rows 6-9 of the lower panel of Table 8.

[43] In the 1850 data, the sample is also limited to males.

[44] There is insufficient data to estimate the returns to literacy in Iowa in 1860. Even in the Iowa Census, there are only 116 illiterate individuals who meet our sample criteria.

Figure A1. Unadjusted Return to Literacy by Year:
US Native-Born Urban Population



Lines show unadjusted gap between the mean ln wage in the average person's occupation (occupational wages in the 1950 Census) between those who report being able to read and write and those who cannot. Data Source: US Censuses of Population (Ruggles et al., 2010). Iowa Census (data source: Goldin & Katz, 2010) shows actual gap in ln(earnings). In all cases, the sample limited to urban native-born residents who are at least age 20. In 1850, the sample is also limited to males.

generate the parameter values, under the continuing assumptions that $\rho = 0.33$, $s_L = 0.08$, and $s_H = 0.51$. Since nesting capital and unskilled labor seems to fit the data better, we will focus on simulations using that nesting.

Panel A of Table 11 simulates the impact of net immigration between 1860 and 1880 using the production function we estimated for that period. Comparing the "actual" to counterfactual ratios of literate to non-literate population, columns 1 and 2 reveal that absent net immigration in this period, skill ratios would actually have been about 8 percent lower.[45] During this era – at least nationally – immigrants had higher literacy rates than natives. According to the parameterization in Table 10 row 7, column 5, removing immigrants who came between 1860 and 1880 would have raised skilled relative wages by about 8 percent, which is equivalent to saying net immigration during that era raised unskilled wages by roughly 8 percent. Capital intensity was also rising during this era, and our complementarity estimates suggest this also would have raised unskilled relative wages. Thus both immigration and technological change during this era likely had the effect of compressing the wage distribution of natives.

The remaining rows of Table 11 examines what would have happened if the U.S. Congress had succeeded in passing a literacy test in 1897.[46] This is done under under two different scenarios: first, using the production function we estimated for 1890-30 in the aggregate (panel B); and second, using the production function we estimated for 1860-80 (panel C). The panel C asks, therefore, what would the impact of the wave of southern and eastern immigration have been if the production technology had not changed?

To implement this simulation, we drop from the census of population sample (Ruggles et al., 2010) any illiterate immigrants who arrived after 1897, and compute the counterfactual skill ratios). Column (2) of Table 11 shows that this raises skill ratios over time, by 1920 substantially, about 35 percent. To do the middle panel simulations, we taking the wage elasticity in row 8 of table 10. Column (4) shows that the literacy test might have lowered skilled relative wages by 7 percent; put differently, the illiterate arrivals who stayed in the U.S. after 1897 appear to have lowered unskilled relative wages by 7 percent. This is quite a modest wage impact given the magnitude of arrivals over this period and the related outcry. The adverse labor market impacts of immigration thus may have been a weak justification for the ultimate passage of a literacy test in 1917, although the sensitivity analysis in the previous section suggests the wage impacts might have been larger than this. However, even these alternatives are quite modest compared to what the relative wage impact would have been true had the production technology in use in the early twentieth century remained the same as it had been 1860-80: using that wage elasticity,

[45] This calculation is made imposing that the same number of literate and illiterate immigrants present in the U.S. in 1860 would have been present in 1880 and native skill mix would have remained the same.

[46] Goldin (1994) investigates the history of attempts to pass immigration restrictions in the U.S. According to her research, 1897 was the first credible attempt to impose a literacy test. In that year, a bill made it through Congress but was vetoed by President Cleveland.

the relative wage impacts would have been over 30 percent. Thus, the new role of capital in production may have played an important role in the absorbtion of large waves of immigrants at the turn of the twentieth century.

7 Conclusions

Our analysis suggests that immigration between 1860 and 1930 was a sufficiently important shock to the local labor force to alter skill ratios in urban counties. It also suggests that manfacturing capital intensity responded to immigration-induced changes in skill ratios (a relationship which holds *within* industry).[47] The estimated responses support the notion that capital relatively substituted for skilled labor in in nineteenth century manufacturing. This appears to have dramatically changed around the turn of the century, when low-skill workers became substitutes for capital and ushering in the level of capital-skill complementarity we see in modern times.

Our analysis potentially suffers from several limitations. First, we have examined a very crude measure of skill composition based on literacy. Not only might this not be a very relevant skill margin – especially towards the end of our period – but it may obscure more subtle relationship between skills and technology, such as the notion that technological advance throughout this period were raising demand for skills as the "poles" of the skill distribution relative to the middle (including Gray, 2013; Katz and Margo, 2013). Some these changes may have taken place outside of the manufacturing sector, the only sector we have data on in this study. Our measure of capital stocks is also very broad, though the same is true of many of the existing U.S. historical studies on manufacturing; we attempted to address this with alternative proxies for machinery use.

We are also only able to directly estimate relative wage impacts using a crude proxy for relative wages; these estimates show little impact. However, simulations based on fitting our estimates to a parametric production function suggest that the small wage impacts we do find are consistent with the adjustments in capital-intensity that we observe. These simulations suggest the importance of the early twentieth century production technology in allowing the U.S. economy to absorb the wave of southern and eastern European migrants with only a modest decline in less-skilled wages. This was possible because the production technology allowed a sufficient rate of substitution away from capital (at a fixed rental rate) in response to the less-skilled labor shock. Under the older production technology in which capital complemented low-skill labor, this would not have been possible. This historical context thus reveals that how non-labor inputs adjust to labor mix shocks plays a critical role in the economy's ability to adapt to the shocks.

[47] We find little support for the idea that shifts in industry mix helped absorb immigrant inflows during the nineteenth and early twentieth centuries.

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Table 1. Descriptive Statistics on Area x Industry Sample

	Early period			Late period		
Variable	# cells	Mean	Std. Dev.	# cells	Mean	Std. Dev.
Panel A: Cut-off in 1880						
ln(K/N)	16668	6.650	0.984	20635	7.217	0.991
ln(K/Y)	16667	-0.105	0.827	20613	0.032	0.724
ln(Fuel/N)	6750	-5.277	1.678	19542	2.916	1.417
ln(Fuel/Y)	6750	-11.907	1.765	19558	-4.288	1.189
ln(Horspower/N)	6750	-5.277	1.678	20497	-0.260	1.242
ln(Horspower/Y)	6750	-11.907	1.765	20516	-7.441	1.119
ln(H/L)	16713	1.921	0.783	23541	2.980	0.687
ln($\widehat{H/L}$)	16713	1.335	0.223	23541	2.204	0.442
Panel B: Cut-off in 1890						
ln(K/N)	22454	6.673	0.960	14849	7.405	0.966
ln(K/Y)	22453	-0.100	0.796	14827	0.077	0.729
ln(Fuel/N)	11784	-2.158	3.953	14508	3.225	1.243
ln(Fuel/Y)	11784	-8.878	3.865	14524	-4.105	1.038
ln(Horspower/N)	12528	-3.143	2.737	14719	-0.107	1.229
ln(Horspower/Y)	12528	-9.860	2.662	14738	-7.430	1.143
ln(H/L)	22500	2.126	0.840	17754	3.065	0.660
ln($\widehat{H/L}$)	22500	1.439	0.264	17754	2.357	0.403
Panel C: Cut-off in 1900						
ln(K/N)	29513	6.728	0.946	7790	7.857	0.812
ln(K/Y)	29495	-0.091	0.782	7785	0.204	0.701
ln(Fuel/N)	18591	-0.406	3.967	7701	3.754	1.029
ln(Fuel/Y)	18605	-7.213	3.836	7703	-3.900	0.919
ln(Horspower/N)	19570	-2.145	2.653	7677	0.134	1.252
ln(Horspower/Y)	19587	-8.949	2.532	7679	-7.518	1.208
ln(H/L)	29559	2.296	0.852	10695	3.217	0.626
ln($\widehat{H/L}$)	29559	1.589	0.359	10695	2.547	0.410

Unweighted means. Skill Ratio is literate/non literate population older than 15, except 1890, which uses published tabulations of the age 10+ population of the area. K includes capital imputed for 1930 from horsepower and *Horsepower* includes imputed horsepower for 1880 and 1890 using machinery and equipment. See Data Appendix.

Table 2. First stage regressions-by period

	Early			Late		
	(1)	(2)	(3)	(4)	(5)	(6)
				Cut-off in 1880		
$\ln(\widehat{H/L})$*Early	1.566***	1.175***	1.172***	-0.406	-0.174	-0.172
	(0.322)	(0.152)	(0.141)	(0.266)	(0.127)	(0.129)
$\ln(\widehat{H/L})$*Late	-0.624***	0.155	0.154	1.383***	0.845***	0.846***
	(0.187)	(0.150)	(0.140)	(0.290)	(0.131)	(0.132)
R^2	0.896	0.931	0.934	0.966	0.984	0.984
				Cut-off in 1890		
$\ln(\widehat{H/L})$*Early	1.266***	1.260***	1.263***	0.000***	0.000	-0.000***
	(0.366)	(0.356)	(0.348)	(0.000)	(0.001)	(0.000)
$\ln(\widehat{H/L})$*Late	-0.000***	0.001	0.000	0.672***	0.679***	0.671***
	(0.000)	(0.003)	(0.000)	(0.229)	(0.229)	(0.232)
R^2	0.933	0.933	0.935	0.990	0.990	0.991
				Cut-off in 1900		
$\ln(\widehat{H/L})$*Early	1.212***	1.073***	1.073***	-0.291*	-0.078	-0.078
	(0.282)	(0.193)	(0.186)	(0.171)	(0.053)	(0.053)
$\ln(\widehat{H/L})$*Late	0.891***	0.030	0.031	0.382*	0.880***	0.882***
	(0.313)	(0.198)	(0.192)	(0.214)	(0.062)	(0.062)
R^2	0.913	0.937	0.939	0.982	0.995	0.995
Fixed Effects:						
Year	Y	Y	Y	Y	Y	Y
Area	Y	Y	Y	Y	Y	Y
Industry	N	Y	Y	N	Y	Y
Ind. x Year	N	N	Y	N	N	Y

Outcome is ln(literate/not literate) in the age 15+ population from IPUMS, except 1890, which uses published tabulations of the age 10+ population of the area. Standard errors in parentheses, calculated to be robust to arbitrary error correlation with area. Sample is restricted to industry-years where at least 2 cities in that year reported a given industry. N=37,278. Significance levels: * 10%, ** 5%, ***1%.

Table 3. Estimation with Aggregate Data

	OLS		IV	
	K/N	K/Y	K/N	K/Y
	(1)	(2)	(3)	(4)
		Cut-off in 1880		
ln(H/L)*Early	0.053	-0.031	0.404**	-0.072
	(0.041)	(0.056)	(0.186)	(0.184)
ln(H/L)*Late	0.038	-0.136	0.467**	-0.057
	(0.066)	(0.129)	(0.199)	(0.194)
RootMSE	0.804	0.721	0.674	0.593
		Cut-off in 1890		
ln(H/L)*Early	0.079**	0.013	0.046	-0.385***
	(0.038)	(0.042)	(0.142)	(0.137)
ln(H/L)*Late	-0.077	-0.385	1.166**	0.556
	(0.144)	(0.334)	(0.553)	(0.469)
RootMSE	0.803	0.718	0.689	0.621
		Cut-off in 1900		
ln(H/L)*Early	0.057	-0.054	0.434**	-0.060
	(0.041)	(0.069)	(0.198)	(0.192)
ln(H/L)*Late	-0.036	-0.191	0.494**	-0.020
	(0.108)	(0.172)	(0.221)	(0.211)
RootMSE	0.804	0.721	0.675	0.594

All outcomes in logs. All regressions include fixed effects by area and by year and are unweighted. Right-hand side variable is ln(literate/not literate) in the age 15+ population (except 1890, which uses published tabulations of the age 10+ population of the area). Standard errors in parentheses, calculated to be robust to arbitrary error correlation with area. N=991. Significance levels: * 10%, ** 5%, ***1%. *K* includes capital imputed for 1930 from horsepower. See Data Appendix.

Table 4. Manufacturing outcomes, **Ordinary Least Squares Estimates**

	Capital/Workers			Capital/Output		
	(1)	(2)	(3)	(4)	(5)	(6)
			Cut-off in 1880			
ln(H/L)*Early	0.053*	0.067***	0.070***	0.023	0.031	0.030
	(0.028)	(0.025)	(0.025)	(0.033)	(0.033)	(0.032)
ln(H/L)*Late	0.104***	0.080***	0.074***	0.059*	0.047*	0.043
	(0.027)	(0.026)	(0.025)	(0.031)	(0.028)	(0.028)
R^2	0.299	0.560	0.610	0.101	0.284	0.353
RootMSE	0.872	0.692	0.658	0.752	0.672	0.645
			Cut-off in 1890			
ln(H/L)*Early	0.071**	0.079***	0.076***	0.035	0.039	0.035
	(0.030)	(0.027)	(0.026)	(0.035)	(0.035)	(0.033)
ln(H/L)*Late	0.069*	0.040	0.051	0.037	0.023	0.029
	(0.035)	(0.034)	(0.032)	(0.032)	(0.031)	(0.029)
R^2	0.299	0.561	0.610	0.101	0.284	0.353
RootMSE	0.872	0.692	0.658	0.752	0.672	0.645
			Cut-off in 1900			
ln(H/L)*Early	0.066***	0.066***	0.066***	0.033	0.033	0.031
	(0.025)	(0.023)	(0.022)	(0.030)	(0.030)	(0.029)
ln(H/L)*Late	0.113***	0.128***	0.125***	0.064*	0.078**	0.066*
	(0.036)	(0.034)	(0.033)	(0.035)	(0.035)	(0.034)
R^2	0.299	0.561	0.610	0.101	0.284	0.353
RootMSE	0.872	0.692	0.658	0.752	0.672	0.645
Fixed Effects:						
Industry	N	Y	Y	N	Y	Y
Ind. x Year	N	N	Y	N	N	Y

All outcomes in logs. All regressions include fixed effects by area and by year and are weighted such that each area-year is given the same weight. Right-hand side variable is ln(literate/not literate) in the age 15+ population (except 1890, which uses published tabulations of the age 10+ population of the area). Standard errors in parentheses, calculated to be robust to arbitrary error correlation with area. Sample is restricted to industry-years where at least 2 cities in that year reported a given industry. N=37,278. Significance levels: * 10%, ** 5%, ***1%. K includes capital imputed for 1930 from horsepower. See Data Appendix.

Table 5. Manufacturing outcomes, **Instrumental Variable Estimates**

	Capital/Worker			Capital/Output		
	(1)	(2)	(3)	(4)	(5)	(6)
				Cut-off in 1880		
ln(H/L)*Early	-0.019	0.037	0.052	-0.159	-0.116	-0.101
	(0.072)	(0.125)	(0.118)	(0.122)	(0.157)	(0.151)
ln(H/L)*Late	0.244*	0.072	0.067	0.042	-0.095	-0.091
	(0.148)	(0.126)	(0.120)	(0.161)	(0.154)	(0.149)
RootMSE	0.870	0.688	0.648	0.751	0.670	0.637
RF F-Stat(Early)	2.337	0.059	0.168	3.165	0.548	0.441
RF F-Stat(Late)	4.512	0.274	0.283	0.892	0.384	0.368
				Cut-off in 1890		
ln(H/L)*Early	-0.136*	-0.032	-0.011	-0.344***	-0.286**	-0.259*
	(0.079)	(0.103)	(0.103)	(0.119)	(0.137)	(0.135)
ln(H/L)*Late	0.516	0.229	0.217	0.472	0.291	0.281
	(0.334)	(0.289)	(0.287)	(0.345)	(0.315)	(0.324)
RootMSE	0.874	0.689	0.649	0.762	0.678	0.643
RF F-Stat(Early)	2.628	0.089	0.011	6.796	3.259	3.132
RF F-Stat(Late)	3.849	0.734	0.680	2.729	1.033	0.929
				Cut-off in 1900		
ln(H/L)*Early	0.083	0.060	0.067	-0.074	-0.103	-0.093
	(0.093)	(0.133)	(0.125)	(0.140)	(0.162)	(0.154)
ln(H/L)*Late	0.244***	0.150	0.148	0.093	-0.053	-0.059
	(0.073)	(0.145)	(0.135)	(0.093)	(0.179)	(0.170)
R^2	0.299	0.561	0.610	0.098	0.280	0.350
RootMSE	0.869	0.688	0.648	0.750	0.670	0.637
RF F-Stat(Early)	0.108	0.163	0.238	0.695	0.419	0.376
RF F-Stat(Late)	3.321	1.054	1.135	0.050	0.090	0.119
Fixed Effects:						
Industry	N	Y	Y	N	Y	Y
Ind. x Year	N	N	Y	N	N	Y

All outcomes in logs. All regressions include fixed effects by area and by year and are weighted such that each area-year is given the same weight. Right-hand side variable is ln(literate/not literate) in the age 15+ population (except 1890, which uses published tabulations of the age 10+ population of the area). Standard errors in parentheses, calculated to be robust to arbitrary error correlation with area. Sample is restricted to industry-years where at least 2 cities in that year reported a given industry. N=37,278. Significance levels: * 10%, ** 5%, ***1%. K includes capital imputed for 1930 from horsepower. See Data Appendix.

Table 6. Alternative capital measures

	Capital/Worker							Capital/Output				
		Fuel exp.			Horsepower			Fuel exp.			Horsepower	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
							Cut-off in 1890					
ln(H/L)*Early	0.042	-0.011	0.021	0.251***	0.108***	0.102***	0.054	0.026	0.048	0.185***	0.074**	0.070**
	(0.058)	(0.036)	(0.040)	(0.039)	(0.028)	(0.030)	(0.058)	(0.039)	(0.043)	(0.041)	(0.033)	(0.034)
ln(H/L)*Late	1.257**	0.681**	0.716**	0.852**	0.059	0.042	1.207**	0.751**	0.795**	0.795*	0.122	0.106
	(0.495)	(0.300)	(0.316)	(0.407)	(0.279)	(0.281)	(0.493)	(0.327)	(0.348)	(0.424)	(0.319)	(0.310)
RootMSE	1.190	0.864	0.826	1.209	0.830	0.740	1.122	0.880	0.843	1.135	0.843	0.756
RF F-Stat(Early)	0.713	0.024	0.020	0.165	0.525	0.211	1.312	0.505	0.571	0.001	0.031	0.004
RF F-Stat(Late)	22.668	11.787	11.912	4.956	0.105	0.021	19.959	14.860	14.037	3.837	0.227	0.112
							Cut-off in 1900					
ln(H/L)*Early	1.077**	0.697**	0.727**	0.773**	0.085	0.064	1.009**	0.764**	0.800**	0.694**	0.140	0.116
	(0.419)	(0.319)	(0.331)	(0.315)	(0.292)	(0.288)	(0.394)	(0.348)	(0.362)	(0.316)	(0.343)	(0.328)
ln(H/L)*Late	0.611**	0.741**	0.760**	0.600***	0.144	0.117	0.497**	0.798**	0.813**	0.475**	0.179	0.140
	(0.247)	(0.347)	(0.360)	(0.187)	(0.316)	(0.311)	(0.230)	(0.380)	(0.394)	(0.186)	(0.381)	(0.361)
RootMSE	1.182	0.866	0.827	1.206	0.830	0.740	1.114	0.881	0.843	1.132	0.843	0.756
RF F-Stat(Early)	8.618	5.494	5.076	3.625	0.554	0.188	5.056	2.884	2.457	2.489	0.261	0.027
RF F-Stat(Late)	13.015	4.804	4.063	7.734	0.908	0.387	6.584	2.263	1.602	4.432	0.342	0.047
Fixed Effects:												
Industry	N	Y	Y	N	Y	Y	N	Y	Y	N	Y	Y
Ind. x Year	N	N	Y	N	N	Y	N	N	Y	N	N	Y

All outcomes in logs. All regressions include fixed effects by area and by year and are weighted such that each area-year is given the same weight. Right-hand side variable is ln(literate/not literate) in the age 15+ population (except 1890, which uses published tabulations of the age 10+ population of the area). Standard errors in parentheses, calculated to be robust to arbitrary error correlation with area. Sample is restricted to industry-years where at least 2 cities in that year reported a given industry. N=19,542 for fuel expenditures and N=20,497 for horsepower. Significance levels: * 10%, ** 5%, ***1%. *Horsepower* includes imputed measures for 1880 and 1890 from machinery and equipment. See Data Appendix.

Table 7. Structural estimate of relative capital-skill complementarity

	Capital			Fuel expenditures			Horsepower		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
					Cut-off in 1880				
κ*Early	0.213**	0.162	0.144						
	(0.100)	(0.156)	(0.150)						
κ*Late	-0.041	0.127	0.129						
	(0.166)	(0.155)	(0.150)						
RF F-Stat(Early)	9.321	1.107	0.934						
RF F-Stat(Late)	0.995	0.698	0.755						
					Cut-off in 1890				
κ*Early	0.360***	0.258**	0.231*	-0.325**	-0.036	-0.013	-0.489***	0.062	-0.011
	(0.111)	(0.131)	(0.131)	(0.162)	(0.099)	(0.106)	(0.177)	(0.142)	(0.040)
κ*Late	-0.384	-0.094	-0.078	-1.250**	-0.626**	-0.669**	-0.769*	0.111	0.134
	(0.353)	(0.318)	(0.314)	(0.518)	(0.306)	(0.321)	(0.457)	(0.358)	(0.345)
RF F-Stat(Early)	10.966	3.329	2.937	1.557	0.457	0.394	0.002	1.405	0.006
RF F-Stat(Late)	1.512	0.089	0.062	16.931	8.319	8.485	2.814	0.154	0.152
					Cut-off in 1900				
κ*Early	0.100	0.140	0.131	-1.067**	-0.637**	-0.673**	-0.709**	0.093	0.121
	(0.134)	(0.163)	(0.154)	(0.422)	(0.321)	(0.332)	(0.350)	(0.373)	(0.355)
κ*Late	-0.160	0.064	0.068	-0.590**	-0.666*	-0.686*	-0.578***	0.052	0.091
	(0.100)	(0.178)	(0.169)	(0.246)	(0.348)	(0.360)	(0.200)	(0.407)	(0.385)
RF F-Stat(Early)	1.856	0.792	0.761	4.349	1.924	1.721	1.631	0.016	0.025
RF F-Stat(Late)	0.051	0.137	0.169	6.950	1.508	1.109	4.188	0.084	0.000
Fixed Effects:									
Industry	N	Y	Y	N	Y	Y	N	Y	Y
Ind. x Year	N	N	Y	N	N	Y	N	N	Y

All regressions include fixed effects by area and by year and are weighted such that each area-year is given the same weight. A corresponds to the ratio of the cross-partial derivative of the production function with respect to capital and illiterate labor over the sum of the cross-partial derivatives with respect to capital and each type of labor. Standard errors in parentheses, calculated to be robust to arbitrary error correlation with area. Sample is restricted to industry-years where at least 2 cities in that year reported a given industry. N=37,278. Significance levels: * 10%, ** 5%, ***1%. K includes capital imputed for 1930 from horsepower and *Horsepower* includes imputed values for 1880-1890 from machinery and equipment. See Data Appendix.

Table 8. Impact on industry composition (share of low-skill workers employed)

	Ranked by their K/L			Ranked by their H/L		
	Q1	Q2	Q3	Q1	Q2	Q3
	(1)	(2)	(3)	(4)	(5)	(6)
			Cut-off in 1880			
ln(H/L)*Early	0.051	-0.029	0.021	-0.026	0.136***	-0.035
	(0.074)	(0.065)	(0.092)	(0.062)	(0.052)	(0.072)
ln(H/L)*Late	0.018	-0.000	0.016	-0.047	0.131**	-0.012
	(0.076)	(0.067)	(0.090)	(0.066)	(0.053)	(0.067)
			Cut-off in 1890			
ln(H/L)*Early	0.017	-0.029	0.053	-0.022	0.163***	-0.073
	(0.084)	(0.064)	(0.119)	(0.057)	(0.059)	(0.079)
ln(H/L)*Late	0.093	0.000	-0.055	-0.055	0.072	0.073
	(0.152)	(0.151)	(0.148)	(0.171)	(0.117)	(0.109)
			Cut-off in 1900			
ln(H/L)*Early	0.034	-0.024	0.024	-0.033	0.138***	-0.026
	(0.070)	(0.069)	(0.092)	(0.061)	(0.053)	(0.070)
ln(H/L)*Late	-0.019	-0.049	0.062	-0.035	0.158***	-0.008
	(0.077)	(0.078)	(0.101)	(0.064)	(0.060)	(0.076)
Average factor ratio	335.006	620.050	955.658	5.627	5.749	5.917

All outcomes in share of low-skill workers employed in each quartile of the distribution of industries. All regressions include fixed effects by area and by year and are unweighted. Right-hand side variable is ln(literate/not literate) in the age 15+ population except 1890, which uses published tabulations of the age 10+ population of the area. Standard errors in parentheses, calculated to be robust to arbitrary error correlation with area. N=884. Significance levels: * 10%, ** 5%, ***1%.

Table 9. Impact on relative wages (skilled/unskilled)

	(1)	(2)	(3)
		Cut-off 1900	
ln(H/L)*Early	0.011	0.011	0.012
	(0.014)	(0.019)	(0.019)
ln(H/L)*Late	-0.000	0.010	0.011
	(0.011)	(0.021)	(0.021)
R^2	0.136	0.223	0.263
RootMSE	0.053	0.050	0.049
Fixed effects:			
Year	Y	Y	Y
Industry	N	Y	Y
Industry x Year	N	N	Y

The outcome variable is Log(literate/illiterate wage). All regressions include fixed effects by area and by year and are weighted such that each area-year is given the same weight. Right-hand side variable is ln(literate/not literate) in the age 15+ population except 1890, which uses published tabulations of the age 10+ population of the area. Standard errors in parentheses, calculated to be robust to arbitrary error correlation with area. Sample is restricted to industry-years where at least 2 cities in that year reported a given industry and to industries-year where some skilled workers were reported. Significance levels: * 10%, ** 5%, ***1%.

Table 10. Impact of a Unit Increase in the ln(Skill Ratio) on the Skilled Wage Premium, Nested CES Production Functions

	Assumed Parameter Values			K Nested w/Unskilled		K Nested w/Skilled	
Source for Parameter Choices:	κ (1)	s_H (2)	s_L (3)	Implied θ (4)	%Impact on skilled wg premium[a] (5)	Implied θ (6)	%Impact on skilled wg premium[a] (7)
				Panel A: Assuming $\rho = 0$			
(1) Benchmark, $\rho = \theta$	$s_L/(s_H + s_L)$	$\in (0,1)$	$\in (0,1)$	0.00	**-1.00**	0.00	**-1.00**
(2) This Paper, 1860-1880	0.30	0.51	0.08	-0.85	**-1.50**	0.58	**-0.92**
(3) This Paper, 1890-1930	-0.10	0.51	0.08	0.77	**-0.29**	N/A[d]	
(4) Lewis (2011a)[c] 1980-2000	-0.15	0.51	0.08	0.90	**-0.14**	N/A[d]	
(5) Autor, Levy, Murnane (2003)	N/A	$\in (0,1)$	$\in (0,1)$	1.00	**0.00**	1.00	**0.00**
				Panel A: Assuming $\rho = 0.33$			
(6) Benchmark, $\rho = \theta$	$s_L/(s_H + s_L)$	$\in (0,1)$	$\in (0,1)$	0.33	**-0.67**	0.00	**-0.67**
(7) This Paper, 1860-80	0.30	0.51	0.08	-0.24	**-1.00**	0.72	**-0.62**
(8) This Paper, 1890-30	-0.10	0.51	0.08	0.85	**-0.19**	N/A[d]	
(9) Lewis (2011a)[c] 1980-2000	-0.15	0.51	0.08	0.93	**-0.09**	N/A[d]	
(10) Variant of (5)	N/A	$\in (0,1)$	$\in (0,1)$	1.00	**0.00**	1.00	**0.00**

Notes: [a]Simulated impact of a one unit increase in $ln(H/L)$, where H represents skilled (literate) and L unskilled (illiterate) labor, on the returns to literacy (skilled-unskilled log wage gap) in a competitive single-good economy represented by the production function (12) in column (5) and (11) in column (7), where K represent capital. This impact is approximated as (16) in column (5) and (15) in column (7) where s_L represents low-skill and s_H skilled labor's share of output, and κ represents the relative cross partial of low-skill labor, estimated in table 7. [b] Estimates of κ from Table 7 are converted to an estimate of θ (for the given value of ρ, s_H and s_L) using (14) when capital is nested with unskilled labor and (13) when capital is nested with skilled labor. [c] Lewis estimates $dln(K/Y)/d(L/H) = -0.56$, (with L, H high school dropouts and completers, respectively) which evaluated at the mean L/H of 0.3 (in Lewis's sample) converts to an elasticity of about $\varepsilon = 0.17$, which is converted to an estimate of κ using that $\kappa = -(\varepsilon - s_L)/(s_L + s_H)$. [d]Negative relative q-complementarity of low-skill labor, κ, is not possible under this parameterization, as it would require $\theta > 1$.

Table 11. Impact of Counterfactual Immigration Flows on Skilled Relative Wage

Year	Counterfactual Scenario	Literate/Not Literate Ratio Actual (1)	Counter-Factual (2)	Gap (in ln) (3)	%Impact on Skilled Relative Wage (4)	Table 8 Wage Elasticity Used (5)
A. Using 1860-80 Estimated Production Function						
1880	No net immigration 1860-80	5.06	4.67	-0.08	**8.15%**	Row 7, Col 5
B. Using 1890-1930 Estimated Aggregate Production Function						
1900	Literacy Test Imposed in 1897	7.94	8.25	0.04	**-0.75%**	Row 8, Col 5
1910	Literacy Test Imposed in 1897	10.17	12.72	0.22	**-4.31%**	Row 8, Col 5
1920	Literacy Test Imposed in 1897	13.58	19.18	0.35	**-6.65%**	Row 8, Col 5
1930	Literacy Test Imposed in 1897	21.03	29.76	0.35	**-6.69%**	Row 8, Col 5
C. Using 1860-80 Estimated Production Function						
1900	Literacy Test Imposed in 1897	7.94	8.25	0.04	**-3.88%**	Row 7, Col 5
1910	Literacy Test Imposed in 1897	10.17	12.72	0.22	**-22.43%**	Row 7, Col 5
1920	Literacy Test Imposed in 1897	13.58	19.18	0.35	**-34.62%**	Row 7, Col 5
1930	Literacy Test Imposed in 1897	21.03	29.76	0.35	**-34.84%**	Row 7, Col 5

Data source for Skill Ratios: U.S. Census of Population (Ruggles et. al 2008). Literacy rates computed for all those (both men and women) who were at least age 15. Counterfactual in panel A constructed by adding together natives present in 1880 with immigrants present in 1860. In Panels B and C, counterfactuals were constructed by dropping illiterate immigrants who reported a year of immigration after 1897 from the sample.

A Derivation of Parametric Model

A.1 Deriving Model of Equation (10)

We know from Equation (4) that the impact of the skill ratio on capital intensity will depend on the cross-partial derivatives of the production function. It is relatively straightforward to show that

$$L\frac{\partial^2 Y}{\partial L \partial K} = (1-\rho)s_L \frac{\partial Y}{\partial K} \tag{17}$$

and that

$$H\frac{\partial^2 Y}{\partial H \partial K} = \frac{\partial Y}{\partial K}\left((1-\theta)s_H + \frac{(\rho-\theta)s_L s_H}{1-s_L}\right) \tag{18}$$

Combining these, we obtain that κ is given by

$$\kappa = \frac{(1-\rho)s_L(1-s_L)}{(1-\rho)s_L(1-s_L-s_H)+(1-\theta)s_H} \tag{19}$$

Let us turn to the first order conditions for L and H to get wages. They are:

$$W_L = A\left(\alpha\left(\beta\left(\frac{K}{H}\right)^{\theta}+(1-\beta)\right)^{\rho/\theta}+(1-\alpha)\left(\frac{L}{H}\right)^{\rho}\right)^{1/\rho-1}(1-\alpha)\left(\frac{L}{H}\right)^{\rho-1} \tag{20}$$

and

$$W_H = A\left(\alpha\left(\beta\left(\frac{K}{H}\right)^{\theta}+(1-\beta)\right)^{\rho/\theta}+(1-\alpha)\left(\frac{L}{H}\right)^{\rho}\right)^{1/\rho-1}\alpha\left(\beta\left(\frac{K}{H}\right)^{\theta}+(1-\beta)\right)^{\rho/\theta-1}(1-\beta). \tag{21}$$

$$\frac{W_H}{W_L} = \frac{\alpha(1-\beta)}{(1-\alpha)}\left(\beta\left(\frac{K}{H}\right)^{\theta}+(1-\beta)\right)^{\rho/\theta-1}\left(\frac{H}{L}\right)^{\rho-1}. \tag{22}$$

This has the log differential form $d\ln(W_H/W_L) = (\rho-\theta)\frac{1-s_L-sH}{1-s_L}d\ln(K/H)+(\rho-1)d\ln(H/L)$.

Substituting in for $d\ln(K/H)$ for $-\kappa d\ln(H/L)$ produces

$$\frac{d\ln(W_H/W_L)}{d\ln(H/L)} = (\rho-\theta)(-\kappa)\frac{1-s_L-sH}{1-s_L} + \rho - 1. \tag{23}$$

A.2 Derivation Model Version 2

In this case:

$$L\frac{\partial^2 Y}{\partial L \partial K} = \frac{(1-\theta)s_L(1-s_H) + (\rho-\theta)s_H s_L}{1-s_H}\frac{\partial Y}{\partial K} \tag{24}$$

and that

$$H\frac{\partial^2 Y}{\partial H \partial K} = \frac{\partial Y}{\partial K}\left((1-\rho)s_H\right) \tag{25}$$

Combining these, we obtain that κ is given by

$$\kappa = \frac{(1-\theta)s_L - (1-\rho)s_H s_L}{(1-\rho)s_H(1-s_L-s_H) + (1-\theta)s_L} \tag{26}$$

Going back to the firm's problem, the first order conditions for high and low skill labor are

$$\begin{aligned}
W_H =& A\left(\alpha\left(\beta\left(\frac{K}{L}\right)^{\theta} + (1-\beta)\right)^{\rho/\theta} + (1-\alpha)\left(\frac{H}{L}\right)^{\rho}\right)^{1/\rho-1}(1-\alpha)\left(\frac{H}{L}\right)^{\rho-1} \\
W_L =& A\left(\alpha\left(\beta\left(\frac{K}{L}\right)^{\theta} + (1-\beta)\right)^{\rho/\theta} + (1-\alpha)\left(\frac{H}{L}\right)^{\rho}\right)^{1/\rho-1}\alpha\left(\beta\left(\frac{K}{L}\right)^{\theta} + (1-\beta)\right)^{\rho/\theta-1}(1-\beta)
\end{aligned}$$

so relative wages are

$$\frac{W_H}{W_L} = \frac{1-\alpha}{\alpha(1-\beta)}\left(\beta\left(\frac{K}{L}\right)^{\theta} + (1-\beta)\right)^{1-\rho/\theta}\left(\frac{H}{L}\right)^{\rho-1}. \tag{27}$$

Taking the log differential of this expression we obtain

$$d\ln(W_H/W_L) = (\theta-\rho)\frac{(1-s_L-s_H)}{1-s_H}d\ln(K/L) + (\rho-1)d\ln(H/L)$$

which, after substituting for $d\ln(K/L) = (1-\kappa)d\ln(H/L)$, becomes

$$d\ln(W_H/W_L) = \left((\theta-\rho)(1-\kappa)(\frac{(1-s_L-s_H)}{1-s_H} + (\rho-1)\right) d\ln(H/L) \tag{28}$$

B Appendix Tables

Table B.1. First stage regressions

	(1)	(2)	(3)
$\ln(\widehat{H/L})$	0.789***	0.784***	0.765***
	(0.166)	(0.159)	(0.149)
R^2	0.874	0.875	0.879
Fixed Effects:			
Year	Y	Y	Y
Area	Y	Y	Y
Industry	N	Y	Y
Ind. x Year	N	N	Y

Outcome is ln(literate/not literate) in the age 15+ population from IPUMS, except 1890, which uses published tabulations of the age 10+ population of the area. Standard errors in parentheses, calculated to be robust to arbitrary error correlation with area. Sample is restricted to industry-years where at least 2 cities in that year reported a given industry. N=37,278. Significance levels: * 10%, ** 5%, ***1%.

Table B.2. Firm size and skill ratios

	Ordinary Least Squares			Instrumental Variables		
	(1)	(2)	(3)	(4)	(5)	(6)
			Cut-off in 1880			
ln(H/L)*Early	0.072	0.118***	0.110***	0.060	0.069	0.048
	(0.155)	(0.028)	(0.027)	(0.157)	(0.106)	(0.115)
ln(H/L)*Late	0.118	0.126***	0.122***	0.143	0.127	0.110
	(0.155)	(0.034)	(0.032)	(0.189)	(0.110)	(0.120)
R^2	0.155	0.367	0.470	0.155	0.367	0.469
RootMSE	1.229	1.070	0.989	1.229	1.064	0.974
			Cut-off in 1890			
ln(H/L)*Early	-0.039	0.146***	0.134***	-0.039	-0.025	-0.062
	(0.208)	(0.031)	(0.030)	(0.208)	(0.119)	(0.132)
ln(H/L)*Late	0.368	0.019	0.032	0.368	0.336	0.364
	(0.311)	(0.044)	(0.042)	(0.311)	(0.310)	(0.328)
R^2	0.151	0.368	0.470	0.151	0.364	0.466
RootMSE	1.232	1.070	0.989	1.232	1.066	0.977
			Cut-off in 1900			
ln(H/L)*Early	0.081	0.125***	0.118***	0.074	0.084	0.064
	(0.155)	(0.026)	(0.026)	(0.145)	(0.108)	(0.116)
ln(H/L)*Late	0.044	0.084**	0.072**	-0.015	0.061	0.031
	(0.176)	(0.038)	(0.034)	(0.099)	(0.127)	(0.134)
R^2	0.155	0.367	0.470	0.155	0.367	0.469
RootMSE	1.229	1.070	0.989	1.229	1.064	0.974
Fixed Effects:						
Industry	N	Y	Y	N	Y	Y
Ind. x Year	N	N	Y	N	N	Y

All outcomes in logs. All regressions include fixed effects by area and by year and are weighted such that each area-year is given the same weight. Right-hand side variable is ln(literate/not literate) in the age 15+ population (except 1890, which uses published tabulations of the age 10+ population of the area). Standard errors in parentheses, calculated to be robust to arbitrary error correlation with area. Sample is restricted to industry-years where at least 2 cities in that year reported a given industry. N=37,408. Significance levels: * 10%, ** 5%, ***1%.