People and Machines
A Look at the Evolving Relationship Between Capital and Skill In Manufacturing 1850-1940 Using Immigration Shocks*

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February 9, 2014

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, we estimate the impact of immigration-induced skill mix changes on input ratios within manufacturing industries using variation across U.S. counties between 1860 and 1940. Combining these estimates and our model, we find evidence that the production functions were strongly altered over the period under study: capital began our period under study as a q-substitute for skilled workers and a strong complement of low-skilled workers. This changed around the turn of the twentieth century when capital became a complement of skilled workers and decreased its complementary with low-skilled workers. We find that within-industry changes in production technique were the dominant manner in which areas adapted to immigration driven skill shocks, and find little change in industry mix. We nevertheless fail to find that the wave of less-skilled immigrants at the turn of the twentieth century significantly affected relative wages. Endogenous adjustments in capital intensity favoring less-skilled employment seem to account for this result.

*We thank Richard Hornbeck, and participants in the First EH/Clio Lab UC Conference, the 2014 AEA Meetings, the 2014 NBER Summer Institute DAE session, the 2014 LACEA Meetings, and seminars at CEA-Univ. de Chile, Maryland, Yale, Northeastern and Colgate for their comments. Tessada acknowledges Fondecyt Grant Iniciación #11110101 and Conicyt Programa de Investigación Asociativa SOC1102 for funding. Lafortune thanks Conicyt Programa de Investigación Asociativa SOC1102. The usual disclaimer applies. We wish to thank Claudia Allende, Rodrigo Carril, Sofía Garcés, Sarah Morse, Francisco Muñoz and Fernanda Rojas for excellent research assistance and to Alejandro Guin-Po Bon, Joaquín Galeno, Miguel Perez, Dominique Araya, Camila Henríquez, Kayla Kesslen, Carla Larín, Mariana Traipe, Una Lee, and Gérard Lafortune for careful data entry.

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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 (Brynjolfsson 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.

[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 employed as a proxy after 1919.

[10]Assuming capital is supplied elastically, the fixed rental rates for capital mute relative wage variation. 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, if capital and skill are complements, this will induce a decline in capital intensity, which raises the relative wage of low skill workers.

Our methodology allows us to control for detailed industry effects, thus removing any confounding factors such as changes in the production mix or other structural trends. Using these controls implies that we are indeed examining changes in factor intensity *within* industry in our preferred specification. This provides an additional 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).[11] 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.

We have four main findings. First, immigration had a significant impact on skill ratios in local labor markets. 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. Second, during the period 1890-1930, capital intensity responded to these skill mix changes in a manner consistent with capital-skill complementarity, and therefore consistent with previous research on early twentieth century manufacturing (Goldin and Katz, 1998).[12] Third, using the same methods and skill mix measure (literacy) we find that capital significantly *substituted* for skilled labor relative to unskilled labor in the period 1860-1880. Finally, shifts in industry mix had a negligible role in absorbing immigrants into local labor markets in either century.[13] Despite the fact that we implicitly find that immigration induces large within-industry changes in skill ratios, we have thus far found little evidence of large relative wage impacts from the flood of less-skilled immigrants at the turn of the twentieth century.[14] Simulations of a parametric production function calibrated to our estimates suggest that endogenous adjustments in capital intensity may account for this.

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] In addition, historians believe immigrants' skills were important in many industrial sectors (Berthoff, 1953).

[12] The response of capital we estimate is not always statistically significant, however. In particular, it is not robust to controls for industry.

[13] 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.

[14] We attempted to directly measure 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 these estimates are potentially confounded by direct compositional impacts.

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).[15] 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.[16] 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."[17] The exact timing may have differed by industry, and of particular interest to us, location.[18] Goldin and Katz (1998) argue and provide evidence that the latter change is associated with greater skill and capital requirements, and so

[15]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".

[16]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).

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

[18]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.

Outline of the paper. In the next section we present a theoretical framework to frame the empirical specifications we estimate later and to illustrate the connection between the different outcomes we look at. In section 3 we describe the empirical specifications and the identification strategy we pursue, and in section 4 we explain our dataset, its construction and the original sources where we obtained the information from. In section 5 we present the results from our estimations, and in section 6 we use a simple version of our theoretical framework to calibrate the estimated impacts of immigration on wage and capital accumulation during the period under study. Finally, in section 7 we present the conclusions and final comments.

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, example Lewis, 2011 and 2013), so let $Y = g(H, L, K)$, where Y is aggregate output.[19] 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,[20]

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

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

[19] 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.

[20] 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.

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. This was the approach to estimating complementarity with capital taken in Lafortune et al. (2013). 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, $N = L + H$. Defining $\phi_h = H/N$, the share of workers who are high skill, the best we can observe in these years is:

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

Note that this relationship is not dispositive for the level of complementarity between capital and either type of labor. As Lewis (2013) emphasizes, for many purposes, we may anyway care more about the *relative* complementarity between capital and high skill and capital and low-skill labor, which, for example, determines the impact of capital deepening on returns to skill (shown below). As he shows, this relative complementarity is positive if and only if capital-labor ratios respond more positively than output-labor ratios to increases in the relative endowment of high skill workers. The response of output-to-low-skill workers is given by:

$$d \ln(Y/L) = \frac{(1 - s_L) H \frac{\partial^2 Y}{\partial K \partial H} + s_H L \frac{\partial^2 Y}{\partial K \partial L}}{H \frac{\partial^2 Y}{\partial K \partial H} + L \frac{\partial^2 Y}{\partial K \partial L}} d \ln(H/L) \tag{4}$$

where $s_H = H(\partial Y / \partial H)/Y$ is high-skill labor's output share and $s_L = L(\partial Y / \partial L)/Y$ is low-skill's share. If high skill and low skill labor are both q-complementary with capital, the output per low-skill labor ratio would increase in response to a shock to high-to-low-skilled endowment ratio. If one labor type is q-complementary and the other is not, the response is ambiguous.[21]

As was already mentioned, whether capital is more complementary with skilled than unskilled labor is revealed by whether the response in (2) or (4) is larger, or, equivalently, by the response of the capital-to-output ratio. A revealing way to write this response is in terms of the

[21] Because measures of H and L are not available in all years in the manufacturing data, we examine instead output per worker, which is given by $d \ln(Y/N) = \frac{(1 - s_L - \phi_h) H \frac{\partial^2 Y}{\partial K \partial H} + (s_H - \phi_h) L \frac{\partial^2 Y}{\partial K \partial L}}{H \frac{\partial^2 Y}{\partial K \partial H} + L \frac{\partial^2 Y}{\partial K \partial L}} d \ln(H/L)$.

response of relative wages:

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

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. For example, if capital and high skill labor are more complementary than capital and low-skill labor, then capital-to-output ratio should rise in response to an increase in the relative endowment of high skill labor. (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 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,

[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.

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 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

$$y_{cit} = \phi \ln \left(\frac{H}{L} \right)_{ct} + \beta X_{ct} + \nu_c + \eta_t + \mu_{it} + \epsilon_{cit} \tag{8}$$

where y_{cit} corresponds to an outcome of interest 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, X_{ct} is a vector of time varying county-level controls and ν_c, η_t, and μ_{it} represent country, time and industry-time fixed effects. Since our interest lies in comparing the evolution of the production function over our sample, we divide it between the early period 1860-1880 and the later period 1890-1940, running all regressions separately by "century". This is based on historical analyses by Chandler (1977) and Jerome (1934) who argue that the Second Industrial Revolution transformed the productive process of manufacturing. All standard errors will be clustered at the geographical level and regressions are weighted as to give each geographical location the same weight.

The interpretation of the coefficient ϕ depends on the relevant outcome that is being estimated (as shown by the equations (2), (4), and (5)). In equation (5), for example, where $ln(K/Y)$ is the outcome, it captures the complementarity between capital and skill relative to capital and low-skill: ϕ will be positive if capital complements skilled labor relative to unskilled labor ($\phi > 0$ implies that $\partial \ln(W_H/W_L)/\partial K > 0$).

An extension of this equation would allow the coefficient ϕ itself to be a function of sector characteristics. This specification can then capture how the impact of a change in factor endowments may differentially affect sectors with different characteristics.

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,

$$y_{ct} = \phi \ln \left(\frac{H}{L} \right)_{ct} + \beta X_{ct} + \nu_c + \eta_t + \epsilon_{ct} \tag{9}$$

In this specification y_{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 suffer 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 critical. 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 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. When the outcome is relative wages, the direction of bias is clear: towards zero, as demand and supply shocks have opposite effects on wages. For capital intensity and the other production outcomes that we examine, the direction of bias is less obvious, but there are reasons to think the bias will also be towards zero. After all, 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] Importantly, positive skill demand shocks outside of manufacturing would tend to push up the wages and employment of skilled workers, while pushing down demand for complementary inputs and production methods in the manufacturing sector (as skilled labor is relatively more expensive) biasing OLS estimates towards zero. Signing bias from local demand shocks within the manufacturing sector is less obvious, but recall that our main approach examines outcomes within industry, and so, again, the main source of demand shocks will likely be outside the sector under observation. OLS estimates might also be attenuated by error in the measurement of skill ratios due to sample variation.[24]

[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.

In any case, we will not rely on OLS, but 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 instrument is given by:

$$\ln(pred\ ratio)_{ct} = ln\left(\frac{\sum_j \left(\frac{N_{jc0}}{N_{j0}} HS\_imm_{jt}\right) + HS\_nat_{c0}\frac{HS\_nat_t}{HS\_nat_0}}{\sum_j \left(\frac{N_{jc0}}{N_{j0}} LS\_imm_{jt}\right) + LS\_nat_{c0}\frac{LS\_nat_t}{LS\_nat_0}}\right) \tag{10}$$

where j represents each country of birth, c (US) county, and t period; N is the stock of immigrants (not broken out by skill); HS_imm_{jt} and LS_imm_{jt} are the *national* stocks of high-skill and low-skill immigrants from each country in each period, respectively; HS_nat_{c0} and LS_nat_{c0} are the stock of natives by skill in some base year, 0; and $\frac{HS\_nat_t}{HS\_nat_0}$ and $\frac{LS\_nat_t}{LS\_nat_0}$ are the *national* growth rates of high and low-skill native-born populations from the base year to t. Note that the first term in the numerator and denominator includes $\frac{N_{jc0}}{N_{j0}}$, which represents the share of immigrants from j living in c as of some base year census. This is used to apportion the current stocks of immigrants by country to locations within the U.S. Thus, the first term in the numerator and denominator represents the number of high- and low-skill immigrants, respectively that would be living in c if immigrants 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 immigrants to counties based on the location of immigrants from one's country 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 this instrument according to approach taken in Smith (2012) to add the predicted skills of natives to the instrument. We predict that from the lagged location of high- and low-skill natives interacted with the national growth rate of skills among native-born workers. Thus, the instrument represents 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. This is done to capture the overall upward trend in skills experienced over this period for natives. However, our current strategy does not allow for some regions to have faster growth in skill levels than the national level, in order to avoid the endogeneity of skill acquisition in response to changes in the manufacturing sector.

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 1850 to 1940 (except in

1890). There are really two options for defining "skill" in these data: occupation or literacy.[25] 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.[26] 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 natives achieved higher rates of growth in literacy than sending countries, making immigration particularly important in determining the illiteracy of the US labor force.

We use immigration as a shock to factor endowment of local labor markets that immigration generates over the period 1860 to 1940. 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 first need a reliable estimate of the location of immigrants of different origins in a "base year" (the $\frac{N_{jc0}}{N_{j0}}$ in (10)). We use two base years for this purpose: 1850, which we apply to the early part of our sample period (1860-1880), and for which we obtained a 100% sample by querying www.ancestry.com and from the preliminary samples of the North Atlantic Population Project; and 1880, which we apply to the the later part of our sample period (1890-1940), and for which a 100% sample is available 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 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. We chose to measure the with the stocks of each types of migrant from each country in 1850 to 1940 by aggregating IPUMS data. 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.[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

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

[26]Literacy is not available in 1940 but in its place we define as "illiterate" anyone who reports fewer than two years of education.

[27]Another option is 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.

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 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]

For the entire period, we can measure a number of outcomes, including the number of workers, the total wage bill, the number of establishments, the value of products, the value of materials and thus also value-added. Capital, one of our key variable, is only available until 1920. However, in 1910, 1920 and 1930, we have horsepower which we use to obtain a proxied of capital for 1930 based on the relationship between horsepower and capital in the two previous decades. From 1890 onwards, we can also distinguish between wage earners and salaried officials, something that we will use to proxy for skilled versus unskilled workers.[32] We have finer definitions of some of the aggregates in a few years (like the division of workers by gender and age, detailed capital or expenses categories) but we are currently not employing those variables in our analysis.

We restrict our sample of analysis to any county for which a city was included in the Census of Manufactures over this period. 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

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

[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 1860-1940 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]This separation matches the one proposed by Goldin and Katz (1998) between what they called production and non-production workers.

industry was appeared in no more than 2 areas in that year.[33] Merged all together, we obtain a very rich panel including 16,492 industry-city-year observations in the early period and 23,665 industry-city-year observations in the late period. This includes a total 179 areas (more in the later period than in the earlier one) and 140 industries (our classification over time generated 150 separate industries but 10 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.

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 differing substantially from natives.

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 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 the of over time in the country composition of immigrants, 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

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

population. That will depend on the particular market under study, but this Figure 2 shows it in the aggregate.

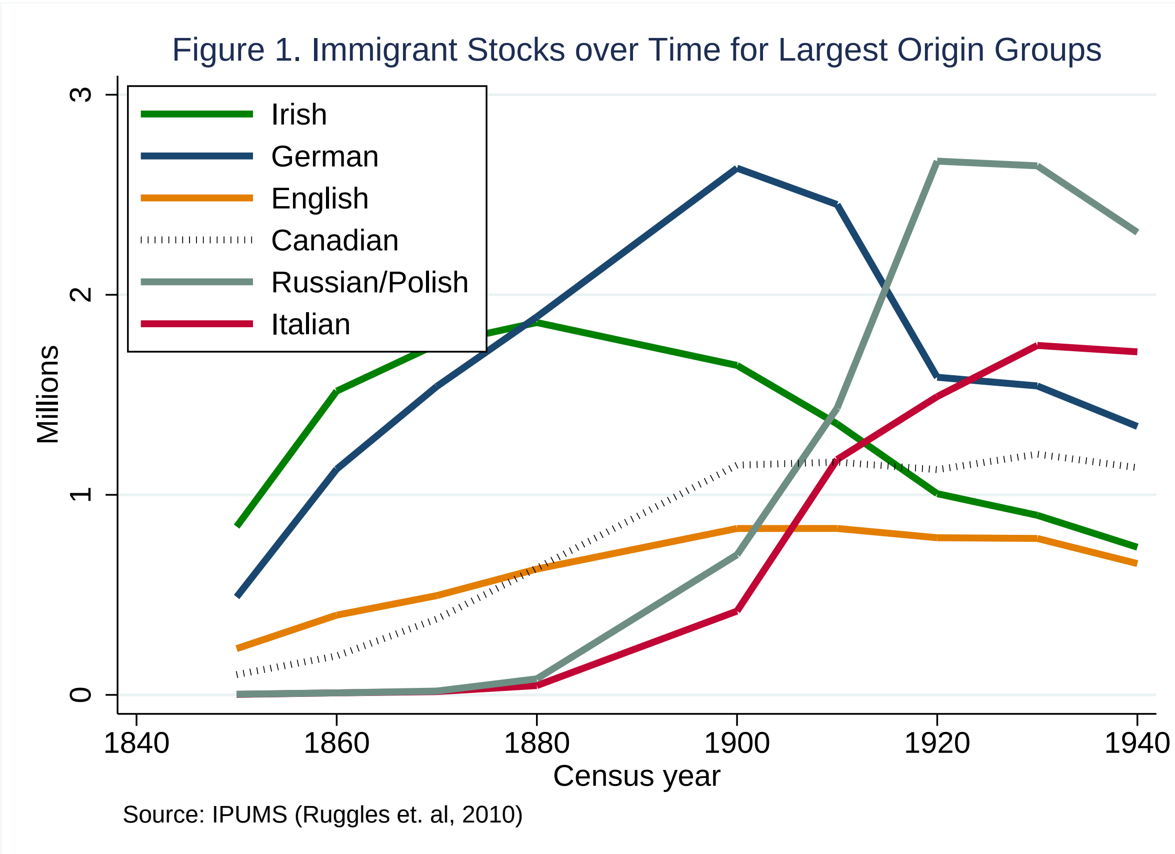
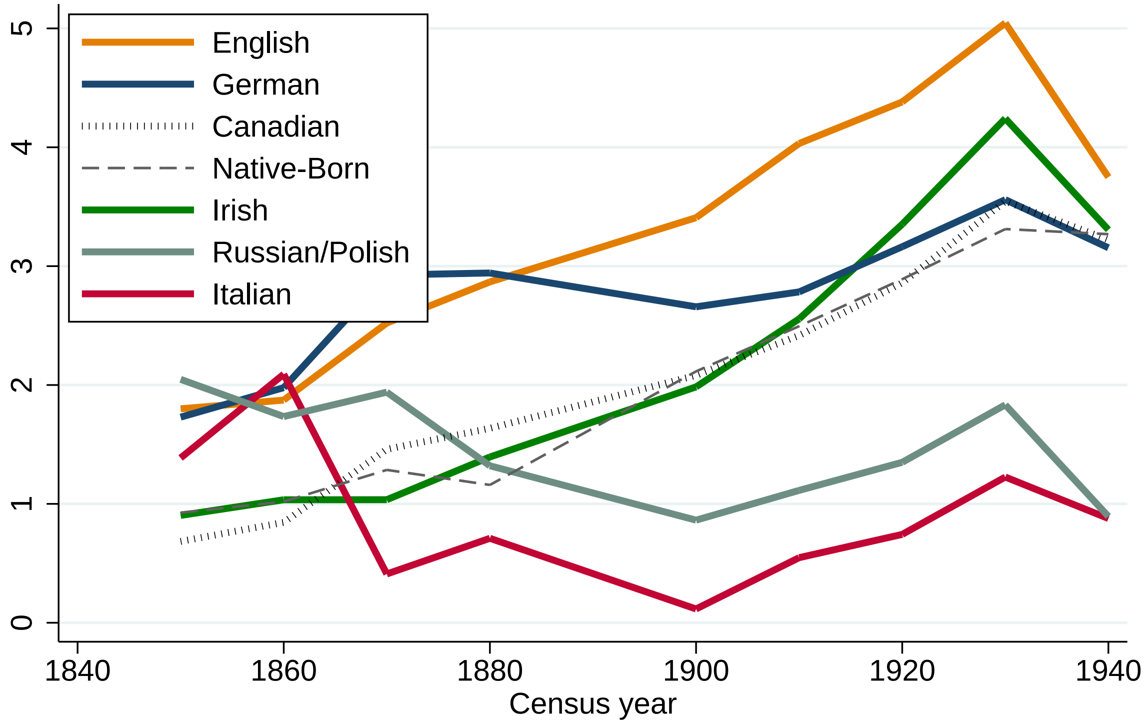


Figure 2 shows the conventional wisdom: German and English immigrants were high skill, so concentrations of them would tend to raise the average skills of workers in an area. In contrast, by the time of the wave of Russian and Italian immigration, these groups had very low literacy skills compared to 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 2 shows the first stage regressions estimated in the industry x county level data. The first column shows the estimate for our full sample. To both account for the fact there are multiple "copies" of county within a year and for the fact that the errors are likely autocorrelated over time, we cluster standard errors on county. In addition, we weight by the inverse of the number of industries represented in a county (to give each county equal weight).[34] Columns 1-3 show the first stage for our early period (1860-80) and columns 4-6 and 7-9 show the first stage, for, respectively, the our two versions of the late period, 1890-1930 and 1890-1940. (The former is because our proxies for capital intensity do not extend beyond 1930.) Within those, the columns

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

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



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

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 2, 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).

In the early period, columns 1-3, the first-stage coefficient is larger than one, but is not significantly different from 1. Recall that one is what you would expect if "predicted" immigration had a one-for-one impact on skill mix. Thus, native migration (or other realized demographic changes) do not appear to offset the impact of predicted immigration on skill ratios. One interpretation of this is that, at least at a decadal time frame, local labor markets were far from perfectly integrated by migration.[35] In the later periods, there may be native outflows, as the first stage coefficient is significantly below 1, at around 0.4-0.5. Across both periods, the first stage is strong, with an F-stat never below 12.

[35] Another possibility is that these inflows had little impact on the wage structure for other reasons.

5.2 Adjustments of Technology

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 (2) examine capital per worker, columns (3) and (4) examine output per worker, and columns (5) and (6) capital per dollar of output. The IV estimates suggest that capital per worker is positively associated with an immigration-induced increase in skill ratios in both our "early" and "late" periods, though it is larger and only significant in the later period. Output per worker rises in skill mix in both periods. But note the contrast in column (5) and (6): capital intensity measured per unit of output *falls* with increases in skill ratios in the early period and rises in the late period. 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 (e.g., Goldin and Katz, 1998). 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.[37] While not 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.

Unsurprisingly, average wages are higher in more skilled areas (columns 9 and 10). (The increases are smaller than those of output per worker, suggesting productivity gains are not entirely accruing to workers.) What would be more interesting is to examine the relative wages of skilled workers. Proxies for that are available, but unfortunately only for part of our period. We will turn to those results below.

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 more capital intensive industries in the early period and less capital intensive ones in the later period, per their association across 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.

[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 additionally 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 plant size.

Table 4 shows ordinary least squares (OLS), and Table 5 shows instrumental variables (IV) estimates of the relationship between skill mix and manufacturing production outcomes at the industry x area level. The top panel of each table shows estimates without any industry effects, the middle panel estimates with industry fixed effects, and the lower panel with fully flexible time-varying industry effects. The table's columns are structured the same way as the previous table.

Let us first consider the IV estimates in Table 5. Without industry effects, capital per worker has a positive, significant association with capital per worker in the later period, but not the earlier one, like in the aggregate results. The magnitude of this later period relationship drops with the inclusion of industry effects, although the confidence intervals overlap. The OLS estimates in Table 4 are positive and significant in both periods. From the model, this suggests, at least, that the data do not rule out that capital q-complements low-skill in both periods, though the IV estimates tend to suggest that the complementarity is stronger in the later period. Turning to columns (3) and (4), the IV estimates suggest a strong association between skills and output per worker in the early period, which is not significantly present in the later period. Combining the two, IV reveals a significant *negative* association between skills and capital per unit output in the early period but not the late period, a result robust to industry controls. Thus, whatever the absolute complementarities, the data continue to strongly suggest that capital was relatively more complementary with low- than high-skill labor, in the 1860-80 period, a result which contrasts sharply with findings in modern manufacturing data and also possibly even in our later period, though those results are admittedly imprecise.

OLS estimates are generally much smaller in magnitude. This, in part, might reflect the much greater precision of these estimates. 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, other unobserved differences might also bias some of the OLS coefficients towards zero. 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.

5.3 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, and prior to that we must rely on tabulated wage data for the categories of workers chosen by the census bureau, which align only somewhat with our skill mix measure.

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, ln(mean wage of salaried officials/mean wage of wage workers). The results using this measure are shown in Table 6. None of the OLS or IV estimates are significant, and the IV estimates are positive. These groups may simply be too far divorced from our skill mix measure to capture any relative wages impacts. In particular, our estimates may be confounded by compositional changes in who makes up salaried officials and wage workers as literacy rates change. In the future, we plan to develop other proxies for relative wages, especially for the early period, as well as use our theoretical model to try to at least simulate wage impacts based on our estimated impact on production outcomes.

5.4 Adjustments of Industry Mix

We now directly explore whether the change in skill availability within an area altered the industry mix. We present, in Table 7, 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 lenghty and difficult to interpret. As a first approximation, we separated industries based on their capital/labor and clerical/production workers ratios at the national level in the first year that variable was provided in the data (namely 1860 for K/L and 1890 for H/L).[38]. We find some evidence that the change in factor availability at the local level also impacted industry composition. Particularly, in cities where the skill ratio increased more rapidly before 1880, industries that were more capital-intensive expanded at the expense of those in the middle of the distribution. No significant impact was observed in the later period of analysis. At the same time, industries that were in the third quartile of skill intensity appear to have shrunk after 1880 while other quartiles expanded, in response to an increase in the 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. Output shift alone would have absorbed, within manufacturing, at most 2 percent of the change in the skill ratio after 1890 and would have actually lowered the skill

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

ratio use between 1860 and 1880. Sectorial shifts would have also lead to at most 2 percent increase in aggregate capital-labor ratio for the later period, a much smaller number than the one presented above. The only case in which there appears to have been an important role for output reallocation is that it led to an increase in the capital-labor ratio of as much as 25 percent between 1860 and 1880. This thus helps us explain why the area-level analysis (Table 3) had a larger point estimates for the response of K/L than the industry x area-level analysis (Table 5). It appears that each industry within manufacturing responded to the skill shock by becoming less capital intensive but this was, in part, undone by a reorientation towards more capital intensive industries. 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.[39] The coefficient for the earlier period is positive and not significant.

6 Parametric Specifications, Calibration and Simulation

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, Ohanian, Rios-Rull and Violante., 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-skill complementarity (and $\rho < \theta$ implies capital and skill are relative substitutes). 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 $\theta > \rho$

[39] Results available upon request.

implies capital-skill complementarity (and $\theta < \rho$ makes capital and skill substitutes). 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 (12):

$$\frac{d\ln(K/Y)}{d\ln(H/L)} \approx \frac{(\theta-\rho)(1-s_H-s_K)s_H}{(\theta-\rho)s_K s_H + (1-\theta)(1-s_H)(1-s_K)}, \tag{13}$$

where s_H is skilled labor's and s_K is capital's share of output. Under capital-skill complementarity, both the numerator and denominator of (13) are positive, and thus capital intensity rises with skill ratios (just as in the general case in section 2). On top of this,

$$\frac{d\ln(W_H/W_L)}{d\ln(H/L)} \approx \frac{(\theta-\rho)(1-\rho)s_H s_K}{(\theta-\rho)s_K s_H + (1-\theta)(1-s_K)(1-s_H)} + \rho - 1. \tag{14}$$

Again, under capital-skill complementarity the first 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, $\rho - 1 < 0$). It is straightforward to produce similar expressions based on (11) as the algebra is symmetric (see appendix).

6.2 Parameter Values

What is the source of the parameter values for our simulations of (13) and (14)? Note that in this paper we have estimated (13) directly, producing IV estimates of roughly -0.3 for 1860-80 and 0.7 for (the aggregate) estimates 1890-1930.[40] These estimates can also be used to solve for one missing parameter, assuming the values of the other parameters. Due to a lack of disaggregated wage data we do not have direct estimates of (14) (although below we will compare our simulations to estimates in Goldin (1994) below). 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. We will then set θ to be consistent with our estimates of (13), subject to assumed values of capital and skilled labor's share.

To see this, Table 8 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-Douglass ($\rho = 0$). As a benchmark, we will start by assuming that capital is neither skilled- nor unskilled complementary, i.e. is "skill neutral," by setting $\theta = \rho = 0$, shown

[40] We will also consider our disaggregate estimates for 1890-1930 below.
[41] This is generalized from a similar table in Lewis (2013).

in row 1.[42] 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 (14).)

Next, let us turn to choosing parameters consistent with our estimate of $\frac{d\ln(K/Y)}{d\ln(H/L)}$ for 1860-80 of -0.3, shown in row 2 of the table. Converting this to an estimate of θ requires assumptions about the values of s_H and s_K. We begin by assuming that $s_K = 0.30$ and $s_H = 0.45$ (which implies that low skill labor's share, $s_L = 0.25$), and do some robustness checks on this below. This implies a large negative value of θ when capital is nested with unskilled labor – implying, plausibly, that capital and unskilled labor had close to a fixed ratio in production. Alternatively, it implies that capital and high skill labor are highly substitutable when capital is nested with skilled 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 nested with skilled labor.

In contrast, as noted in 2, if the response of capital output ratios to skill mix is positive – so that capital and skill are relative complements – then the relative wage impacts are smaller than the benchmark case. Taking our aggregate estimate of $\frac{d\ln(K/Y)}{d\ln(H/L)} = 0.7$ for 1890-1930 in row (3) we find that wage impacts are, in fact, one-sixth as large in magnitude as predicted by the simple Cobb-Douglass elasticity of substitution, when capital nests with unskilled labor. This is because this estimate implies capital and unskilled labor are near perfect substitutes ($\theta = 0.94$, just less than one), so relative wages are pinned down by the (exogenous) price of capital. No reasonable parameter values fit the alternative nesting in this case, which perhaps casts some doubt on its appropriateness. On the other hand, perhaps 0.7 possibly is too large a capital intensity response. In modern data and using a similar approach, Lewis (2011) estimates a capital response of 0.17 (albeit for different skill categories, high school dropouts and completers), which is close to the estimate we obtain in the disaggregate data without controlling for industry effects.[43] Using this instead implies a more modest twenty percent reduction in the magnitude of relative wage impacts (row 4). Finally, row 5 repeats another extreme benchmark from section 2, the case from Autor et al. (2003) in which capital and a labor input are perfect substitutes, in which case there is zero wage impact.

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

[42] $\theta = \rho$ is also consistent with our disaggregate estimates for 1890-30.

[43] When we include the industry effects, recall, the capital intensity response is closer to zero. This case is already covered in row 1 of the table.

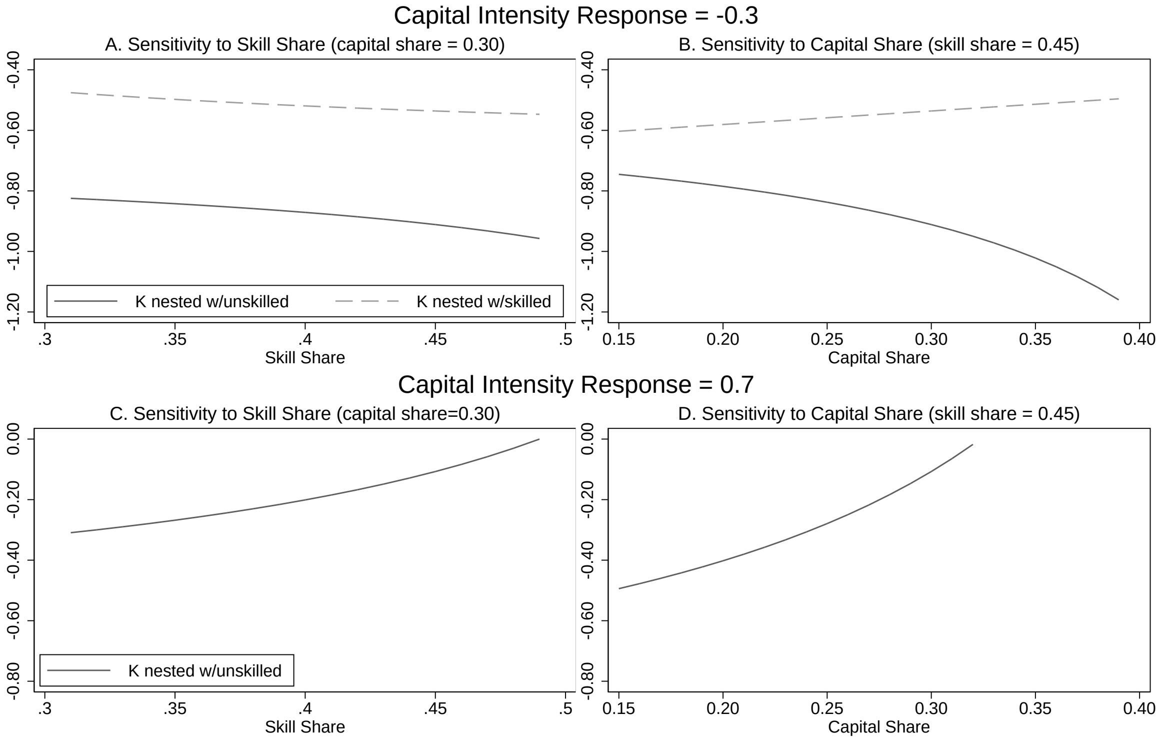
smaller in this panel (by design of the larger elasticity), but the proportional difference across rows varies in nearly the same way as the upper panel (for example, the estimates in row 8 are about one-sixth big as in row 6). The same pattern emerges consistently for other values of ρ (not shown in table).

What about the values of s_K and s_H? In their simulations, Taylor and Williamson (1997) assume labor's share is 0.6 in the broader economy, citing a number of studies. Capital's share is likely not likely as large as 0.4 in manufacturing, especially early in our sample. For one thing, land has a minor role in manufacturing but is important in the broader economy. In addition, raw capital / value added ratios rise from 1-2 over the period of our study, so without assuming an implausibly large rate of interest or depreciation, it seems reasonably safe to assume that capital has a flow value of $s_K < 0.4$.[44] Finally, it turns out that obtaining values of θ in an appropriate range, especially when $\frac{d\ln(K/Y)}{d\ln(H/L)} = -0.3$, also bounds s_K below 0.4.[45] Figure 3 shows some simulations with different values of s_H and s_K. It shows shares do matter for relative wage impacts. It shows that wage impacts would be even smaller in magnitude if capital or skill shares were larger in the later period, which they might have been. The opposite is true in the early period.

[44]One caveat on this it is hard to show that labor's share is that high. Wage bill/value added is never above 0.5 in our data; this may not capture labor's share of output, however.

[45]In order for $\theta < 1$, we need that $s_H + \frac{d\ln(K/Y)}{d\ln(H/L)} > 0$ when capital is nested with unskilled labor and $1 - s_H - s_K - \frac{d\ln(K/Y)}{d\ln(H/L)} > 0$ when capital is nested with skilled labor. So if $\frac{d\ln(K/Y)}{d\ln(H/L)} = -0.3$, we need that s_K<0.4, since we need $s_H + s_K < 0.7$ and $s_H > 0.3$. See appendix.

Figure 3. Relative Wage Response to Skill Mix: Sensitivity to Share Parameters



Simulated relative wage impact of a one unit change in skill ratios under nested CES production function with capital, skilled and unskilled labor Capital intensity response refers to the response of capital-output ratios to proportional changes in skill ratios. Rho parameter (elasticity of substituion between skilled and unskilled) is assumed to be 0.33. Simulations for CES inner nest with capital and skilled labor infeasible when the capital intensity response is 0.7.

Interestingly, the estimates in the lower panel of Table 8 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.[46] Given the large 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.

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

6.3 Simulating the Impact of Immigration

The one unit increase in $ln(H/L)$ used in the Table 8 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 9 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 generate the parameter values, under the continuing assumptions that $\rho = 0.33$, $s_K = 0.30$, and $s_H = 0.45$. Since nesting capital and unskilled labor seems to fit the data better, we will focus on simulations using that nesting.

Panel A of Table 9 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.[47] During this era – at least nationally – immigrants had higher literacy rates than natives. According to the parameterization in Table 8 row 7, column 5, removing immigrants who came between 1860 and 1880 would have raised skilled relative wages by about 7 percent, which is equivalent to saying net immigration during that era raised unskilled wages by roughly 7 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.[48]

The remaining rows of Table 9 examines what would have happened if the U.S. Congress had succeeded in passing a literacy test in 1897.[49] 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 drops 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 9 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 8. Column (4) shows that the literacy test might have lowered skilled relative wages by

[47]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.

[48]Not shown in the table is the fact that, according to our estimates, immigration-induced changes skill ratio account for about one-fifth of the 12 percent rise in capital intensity over the period 1860-80.

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

4 percent; put differently, the illiterate arrivals who stayed in the U.S. after 1897 appear to have lowered unskilled relative wages by 4 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, 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 1940 was a sufficiently important shock to the local labor force to alter skill ratios in urban counties. It also suggests that the capital stock, output, and average wages all responded to immigration-induced changes in skill ratios, a relationship which holds *within* industry as well and in the aggregate. These estimated responses provide strong support for the notion that capital and skill were *substitutes* in nineteenth century manufacturing, something which appears to have dramatically changed around the turn of the century. Finally, we find little support for the idea that shifts in industry mix helped absorb immigrant inflows during the nineteenth and early twentieth centuries.

Our analysis 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). 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. Finally, we have have thus far been only able to study relative wage impacts using a fairly crude proxy. Nevertheless, simulations based on our estimates suggest that the small wage impacts we have found are consistent with the adjustments in capital-intensity that we observe.

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Table 1. Descriptive Statistics on Area x Industry Sample

Variable	Early period: 1860-1880			Late period: 1890-1940		
	# cells	Mean	Std. Dev.	# cells	Mean	Std. Dev.
1860-1930:						
ln(Capital/Worker)[a]	16915	6.654	0.982	21321	7.238	0.987
ln(Output/Worker)	16912	7.484	0.793	21299	7.842	0.759
ln(Capital/Output)[a]	16912	-0.830	0.769	21299	-0.607	0.691
1860-1940:						
ln(Workers/Establishment)	16915	2.248	1.202	24287	2.608	1.359
ln(Wage/worker)	16915	5.896	0.496	24277	6.242	0.705
1910-1930:						
ln(Horsepower)		N/A		8003	5.785	2.239
Area Level Variables:						
ln(Skill Ratio)	16915	1.927	0.787	24296	2.979	0.689
Instrument (skill ratio)	16915	1.335	0.222	24296	2.207	0.443

Unweighted means. There are 129 industries in the full sample. In the early period there are 117 areas, while in the late period there are 169. Skill Ratio is literate/non literate population older than 15, except 1890, which uses published tabulations of the age 10+ population of the area, and 1940, which uses persons with fewer than two years of education to proxy for illiteracy. [a]Includes capital imputed for 1930 from horsepower as ln(K) = 0.77899475xln(Hp), estimated using 1910-1920 city x industry data. See Data Appendix.

Table 2. First stage regressions

	1860-80			1890-1930			1890-1940		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Predicted	1.533***	1.485***	1.476***	0.356**	0.358**	0.332**	0.438***	0.439***	0.412***
	(0.517)	(0.483)	(0.472)	(0.154)	(0.154)	(0.150)	(0.136)	(0.135)	(0.131)
r2	0.790	0.793	0.800	0.866	0.867	0.870	0.842	0.844	0.848
N	16,912	16,912	16,912	21,299	21,299	21,299	24,296	24,296	24,296
Fixed Effects:									
Year	Y	Y	Y	Y	Y	Y	Y	Y	Y
Area	Y	Y	Y	Y	Y	Y	Y	Y	Y
Industry	N	Y	Y	N	Y	Y	N	Y	Y
Ind. x Year	N	N	Y	N	N	Y	N	N	Y

Outcome is ln(literate/not literate) in the age 15+ population computed using Ruggles et al. (2010), except 1890, which uses published tabulations of the age 10+ population of the area, and 1940, which uses persons with fewer than two years of education to proxy for illiteracy. Standard errors in parentheses, calculated to be robust to arbitrary error correlation with area (=county, except for New York City). Sample is restricted to industry-years where at least 2 cities in that year reported a given industry. Significance levels: * 10%, ** 5%, ***1%.

Table 3. Estimation with Aggregate Data

	Capital/Worker[a]		Output/Worker		Capital/Output[a]		Workers/Estab		Wages/Worker	
	1860-80	1890-1930	1860-80	1890-1930	1860-80	1890-1930	1860-80	1890-1940	1860-80	1890-1940
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
					Ordinary Least Squares					
ln(skill ratio)	0.093**	0.037	0.043	0.047	0.050	-0.028	0.150**	-0.011	0.073***	-0.019
	(0.047)	(0.060)	(0.047)	(0.050)	(0.055)	(0.046)	(0.064)	(0.050)	(0.026)	(0.049)
R^2	0.617	0.909	0.599	0.422	0.525	0.960	0.822	0.840	0.750	0.346
RootMSE	0.268	0.944	0.288	0.782	0.303	0.661	0.381	0.326	0.186	0.791
					Instrumental Variables					
ln(skill ratio)	0.280	1.242**	0.713**	0.790*	-0.433**	0.735*	0.024	0.697**	0.209	0.382*
	(0.240)	(0.533)	(0.341)	(0.404)	(0.173)	(0.394)	(0.378)	(0.292)	(0.225)	(0.230)
R^2	0.555	0.893	-0.121	0.363	0.124	0.954	0.816	0.746	0.705	0.326
RootMSE	0.226	0.876	0.377	0.701	0.322	0.605	0.304	0.357	0.158	0.699
F-stats:										
Red. Form	1.735	4.092	6.603	2.616	3.549	2.985	0.049	5.687	1.945	2.100
First Stage	8.41	10.73	8.41	10.73	8.41	10.73	8.41	15.59	8.41	15.59
N	341	650	341	650	341	650	341	736	341	736

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, and 1940, which uses persons with fewer than two years of education to proxy for illiteracy. Standard errors in parentheses, calculated to be robust to arbitrary error correlation with area (=county, except New York City). Significance levels: * 10%, ** 5%, ***1%. [a]Includes capital imputed for 1930 from horsepower as ln(K) = 0.77899475xln(Hp), estimated using 1910-1920 city x industry data. See Data Appendix.

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

	Capital/Worker[a]		Output/Worker		Capital/Output[a]		Workers/Estab		Wages/Worker	
	1860-80	1890-1930	1860-80	1890-1930	1860-80	1890-1930	1860-80	1890-1940	1860-80	1890-1940
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
No Industry Effects										
ln(skill ratio)	0.071*	0.069***	0.035	0.047***	0.035	0.021	0.148***	0.014	0.044***	0.031
	(0.036)	(0.023)	(0.032)	(0.015)	(0.044)	(0.019)	(0.041)	(0.032)	(0.016)	(0.038)
R^2	0.054	0.332	0.098	0.403	0.063	0.088	0.138	0.138	0.164	0.383
RootMSE	0.951	0.813	0.740	0.579	0.771	0.685	1.104	1.287	0.472	0.557
With Industry Effects										
ln(skill ratio)	0.076**	0.041*	0.035*	0.031**	0.041	0.010	0.147***	0.024	0.044***	0.027
	(0.033)	(0.022)	(0.021)	(0.014)	(0.041)	(0.019)	(0.034)	(0.029)	(0.016)	(0.038)
R^2	0.418	0.597	0.526	0.684	0.222	0.330	0.386	0.391	0.302	0.462
RootMSE	0.751	0.635	0.541	0.423	0.708	0.590	0.939	1.087	0.435	0.523
With Industry x Year Effects										
ln(skill ratio)	0.072**	0.041*	0.036*	0.032**	0.036	0.009	0.146***	0.051*	0.045***	0.030
	(0.033)	(0.022)	(0.019)	(0.014)	(0.039)	(0.020)	(0.034)	(0.026)	(0.015)	(0.037)
R^2	0.437	0.644	0.547	0.706	0.249	0.409	0.425	0.493	0.334	0.492
RootMSE	0.744	0.602	0.532	0.412	0.700	0.559	0.914	1.002	0.427	0.512
N	16,491	20,615	16,491	20,615	16,491	20,615	16,494	23,539	16,494	23,531

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, and 1940, which uses persons with fewer than two years of education to proxy for illiteracy. Standard errors in parentheses, calculated to be robust to arbitrary error correlation with area (=county, except New York City). Sample is restricted to industry-years where at least 2 cities in that year reported a given industry. Significance levels: * 10%, ** 5%, ***1%. [a]Includes capital imputed for 1930 from horsepower as ln(K) = 0.77899475xln(Hp), estimated using 1910-1920 city x industry data. See Data Appendix.

Table 5. Manufacturing outcomes, **Instrumental Variables Estimates**, By Century

	Capital/Worker[a]		Output/Worker		Capital/Output[a]		Workers/Estab		Wages/Worker	
	1860-80	1890-1930	1860-80	1890-1930	1860-80	1890-1930	1860-80	1890-1940	1860-80	1890-1940
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
No Industry Effects										
ln(skill ratio)	-0.106	0.353**	0.296**	0.198**	-0.402***	0.154	0.147	0.456***	0.166	0.114
	(0.098)	(0.159)	(0.119)	(0.080)	(0.152)	(0.135)	(0.220)	(0.143)	(0.117)	(0.082)
R^2	0.047	0.325	0.074	0.399	-0.001	0.085	0.138	0.128	0.152	0.381
RootMSE	0.954	0.817	0.750	0.581	0.797	0.686	1.104	1.294	0.475	0.557
With Industry Effects										
ln(skill ratio)	-0.118	0.075	0.280**	0.121	-0.398***	-0.047	0.112	0.363***	0.216*	0.100
	(0.127)	(0.134)	(0.131)	(0.075)	(0.152)	(0.127)	(0.172)	(0.123)	(0.123)	(0.077)
R^2	0.410	0.597	0.506	0.683	0.159	0.330	0.385	0.385	0.279	0.461
RootMSE	0.751	0.631	0.548	0.422	0.731	0.587	0.932	1.087	0.439	0.520
With Industry x Year Effects										
ln(skill ratio)	-0.068	0.076	0.300**	0.074	-0.368**	0.002	0.129	0.442***	0.234**	0.115
	(0.126)	(0.139)	(0.131)	(0.077)	(0.151)	(0.137)	(0.174)	(0.124)	(0.117)	(0.078)
R^2	0.433	0.644	0.524	0.706	0.198	0.409	0.425	0.485	0.307	0.491
RootMSE	0.736	0.593	0.538	0.406	0.713	0.551	0.902	0.994	0.430	0.505
N (from Table6-3b.txt)	16,912	21,299	16,912	21,299	16,912	21,299	16,915	24,287	16,915	24,277

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, and 1940, which uses persons with fewer than two years of education to proxy for illiteracy. Standard errors in parentheses, calculated to be robust to arbitrary error correlation with area (=county, except New York City). Sample is restricted to industry-years where at least 2 cities in that year reported a given industry. Significance levels: * 10%, ** 5%, ***1%. [a]Includes capital imputed for 1930 from horsepower as ln(K) = 0.77899475xln(Hp), estimated using 1910-1920 city x industry data. See Data Appendix.

Table 6. Impact on relative wages (skilled/unskilled), 1890-1940

	(1)	(2)	(3)
	Ordinary Least Squares		
ln(skill ratio)	-0.026	-0.033	-0.029
	(0.054)	(0.054)	(0.054)
R^2	0.165	0.088	0.212
RootMSE	0.571	0.596	0.561
	Instrumental Variables		
ln(skill ratio)	0.094	0.145	0.107
	(0.110)	(0.114)	(0.121)
R^2	0.161	0.079	0.207
RootMSE	0.569	0.596	0.553
N	22,345	22,345	22,345
Fixed effects:			
Year	Y	Y	Y
Industry	N	Y	Y
Industry x Year	N	N	Y

The outcome variable is Log(wage salaried officials/wage production workers). 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, and 1940, which uses persons with fewer than two years of education to proxy for illiteracy. Standard errors in parentheses, calculated to be robust to arbitrary error correlation with area (=county, except New York City). 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 7. Impact on industry composition (share of low-skill workers employed)

	First quartile		Second quartile		Third quartile	
	1860-80	1890-1940	1860-80	1890-1940	1860-80	1890-1940
	(1)	(2)	(3)	(4)	(5)	(6)
	Industries ranked by their K/L					
ln(skill ratio)	0.031	0.043	-0.056	-0.090	0.050	-0.092
	(0.106)	(0.065)	(0.078)	(0.088)	(0.173)	(0.087)
Average K/L	353.873		623.353		953.816	
	Industries ranked by their H/L					
ln(skill ratio)	-0.000	-0.087	0.145*	-0.075	-0.040	-0.045
	(0.066)	(0.099)	(0.077)	(0.060)	(0.061)	(0.065)
Average H/L	0.042		0.085		0.141	
N	328	635	328	635	328	635

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, and 1940, which uses persons with fewer than two years of education to proxy for illiteracy. Standard errors in parentheses, calculated to be robust to arbitrary error correlation with area (=county, except New York City). Significance levels: * 10%, ** 5%, ***1%. First stage F-stat = 1860-80, ; 1890-1930, ; 1890-1940, .

Table 8. Impact of a Unit Increase in the ln(Skill Ratio) on the Skilled Wage Premium, Nested CES Production Functions

Source for Parameter Choices	Assumed Parameter Values: K-intensity response: $\frac{d\ln(K/Y)}{d\ln(H/L)}$	Assumed Parameter Values: Skilled output share s_H	Assumed Parameter Values: Capital output share s_K	K Nested w/Unskilled: Implied Value for…[b] θ	K Nested w/Unskilled: %Impact on skilled wg premium[a]	K Nested w/Skilled: Implied Value for…[b] θ	K Nested w/Skilled: %Impact on skilled wg premium[a]
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	$\rho = 0$ (Cobb-Douglass) $\rightarrow s_H = 1-\alpha$					$\rho = 0 \rightarrow s_H+s_K = \alpha$	
(1) Benchmark: Capital is skill neutral, $\rho=\theta$	0.00	$\in(0,1)$	$\in(0,1)$	0.00	**-1.00**	0.00	**-1.00**
(2) This Paper, 1860-80	-0.30	0.45	0.30	-3.08	**-1.36**	0.64	**-0.80**
(3) This Paper, 1890-1930 (aggregate)	0.70	0.45	0.30	0.94	**-0.16**	N/A[d]	
(4) Lewis (2011a),[c] 1980-2000	0.17	0.45	0.30	0.42	**-0.80**	-2.48	**-1.11**
(5) Benchmark: Autor, Levy, Murnane (2003)	N/A	$\in(0,1)$	$\in(0,1)$	1.00	**0.00**	1.00	**0.00**
	$\rho = 0.33$					$\rho = 0.33$	
(6) Benchmark: Capital is skill neutral, $\rho=\theta$	0.00	$\in(0,1)$	$\in(0,1)$	0.33	**-0.67**	0.00	**-0.67**
(7) This Paper, 1860-80	-0.30	0.45	0.30	-1.73	**-0.91**	0.76	**-0.54**
(8) This Paper, 1890-30 (aggregate)	0.70	0.45	0.30	0.96	**-0.11**	N/A[d]	
(9) Lewis (2011a),[c] 1980-2000	0.17	0.45	0.30	0.61	**-0.53**	-1.33	**-0.75**
(10) Benchmark: 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 $Y=[\alpha(\beta K^{\theta}+(1-\beta)H^{\theta})^{\rho/\theta}+(1-\alpha)L^{\rho}]^{1/\rho}$ in column (5) and $Y=[\alpha(\beta K^{\theta}+(1-\beta)L^{\theta})^{\rho/\theta}+(1-\alpha)H^{\rho}]^{1/\rho}$ in column (7), where K represent capital. This impact is approximated as $(\theta-\rho)(1-\rho)s_H s_K/[(\theta-\rho)s_K s_H+(1-\theta)(1-s_H)(1-s_K)]+\rho-1$ in column (5) and $(\theta-\rho)(1-\rho)(1-s_H-s_K)s_K/[(\theta-\rho)s_K(1-s_H-s_K)+(1-\theta)(s_H+s_K)(1-s_K)]+\rho-1$ in column (7) where s_K represents capital's share and s_H skilled labor's share of output. [b]Estimates of dln(K/Y)/dln(H/L) are converted to an estimate of θ (for the given value of ρ, s_H and s_K) using the fact that $d\ln(K/Y)/d\ln(H/L) \approx (\theta-\rho)(1-s_H-s_K)s_H/[(\theta-\rho)s_K s_H+(1-\rho)(1-s_H)(1-s_K)]$ (for the nesting used in columns 4-5) and $(\theta-\rho)(1-s_H-s_K)s_H/[(\theta-\rho)s_K(1-s_H-s_K)+(1-\theta)(s_H+s_K)(1-s_K)]$ (for the nesting used in columns 6-7), except in rows 1,5,6 and 10 where it comes from assumptions, rather than an estimates. [c]Lewis estimates dln(K/Y)/d(L/H) = -0.56, (with L,H high school dropouts and completers, respectively) which evaluted at the mean L/H of 0.3 converts to an elasticity of about 0.17. [d]To obtain an estimated capital intensity response of 0.7 would require that $s_H+s_K<0.3$ under this parameterization, which is not credible.

Table 9. Impact of Counterfactual Immigration Flows on Skilled Relative Wage

Year	Counterfactual Scenario	Literate/Not Literate Ratio: Actual	Counter-Factual	Gap (in ln)	%Impact on Skilled Relative Wage	Table 8 Wage Elasticity Used
		(1)	(2)	(3)	(4)	(5)
A. Using 1860-80 Estimated Production Function						
1880	No net immigration 1860-80	5.06	4.67	-0.08	**7.40%**	Row 7, Col 5
B. Using 1890-1930 Estimated Aggregate Production Function						
1900	Literacy Test Imposed in 1897	7.94	8.25	0.04	**-0.41%**	Row 8, Col 5
1910	Literacy Test Imposed in 1897	10.17	12.72	0.22	**-2.40%**	Row 8, Col 5
1920	Literacy Test Imposed in 1897	13.58	19.18	0.35	**-3.70%**	Row 8, Col 5
1930	Literacy Test Imposed in 1897	21.03	29.76	0.35	**-3.72%**	Row 8, Col 5
C. Using 1860-80 Estimated Production Function						
1900	Literacy Test Imposed in 1897	7.94	8.25	0.04	**-3.53%**	Row 7, Col 5
1910	Literacy Test Imposed in 1897	10.17	12.72	0.22	**-20.37%**	Row 7, Col 5
1920	Literacy Test Imposed in 1897	13.58	19.18	0.35	**-31.45%**	Row 7, Col 5
1930	Literacy Test Imposed in 1897	21.03	29.76	0.35	**-31.65%**	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 Version 1

This section derives the parametric model used in the simulations in section 6. Begin with a rewritten version of the production function in (11):

$$Y = A\left(\alpha\left(\beta\left(\frac{K}{H}\right)^{\theta}+(1-\beta)\right)^{\rho/\theta}+(1-\alpha)\left(\frac{L}{H}\right)^{\rho}\right)^{1/\rho} H \tag{15}$$

The first order condition for capital, assuming an exogenous price r, is:

$$r = A\left(\alpha\left(\beta\left(\frac{K}{H}\right)^{\theta}+(1-\beta)\right)^{\rho/\theta}+(1-\alpha)\left(\frac{L}{H}\right)^{\rho}\right)^{1/\rho-1}\alpha\left(\beta\left(\frac{K}{H}\right)^{\theta}+(1-\beta)\right)^{\rho/\theta-1}\beta\left(\frac{K}{H}\right)^{\theta-1} \tag{16}$$

So capital's share of output is given by

$$s_K = \frac{rK}{Y} = \left(\alpha\left(\beta\left(\frac{K}{H}\right)^{\theta}+(1-\beta)\right)^{\rho/\theta}+(1-\alpha)\left(\frac{L}{H}\right)^{\rho}\right)^{-1}\alpha\left(\beta\left(\frac{K}{H}\right)^{\theta}+(1-\beta)\right)^{\rho/\theta-1}\beta\left(\frac{K}{H}\right)^{\theta} \tag{17}$$

We can log linearlize (16) and impose that $d\ln r = 0$ to solve for equilibrium $d\ln\left(\frac{K}{H}\right)$ as a function of $d\ln\left(\frac{H}{L}\right)$, in several steps. $0 = (1/\rho-1)d\ln\left(\alpha\left(\beta\left(\frac{K}{H}\right)^{\theta}+(1-\beta)\right)^{\rho/\theta}+(1-\alpha)\left(\frac{L}{H}\right)^{\rho}\right)+(\rho/\theta-1)d\ln\left(\beta\left(\frac{K}{H}\right)^{\theta}+(1-\beta)\right)+(\theta-1)d\ln\left(\frac{K}{H}\right)$ We can rewrite this as a log linear approximation using low-skill and capital factor shares s_L and s_K.[50]

$$0 \approx (1/\rho-1)\left((1-s_L)\frac{s_K}{1-s_L}\rho d\ln\frac{K}{H}+s_L\rho d\ln\frac{L}{H}\right)+(\rho/\theta-1)\frac{s_K}{1-s_L}\theta d\ln\frac{K}{H}+(\theta-1)d\ln\frac{K}{H},$$

which simplifies to

$$0 \approx (1-\rho)s_K d\ln\frac{K}{H}+(1-\rho)s_L d\ln\frac{L}{H}+(\rho-\theta)\frac{s_K}{1-s_L}d\ln\frac{K}{H}+(\theta-1)d\ln\frac{K}{H}$$

or

$$\frac{(1-\rho)s_K(1-s_L)+(\rho-\theta)s_K+(\theta-1)(1-s_L)}{1-s_L}d\ln\frac{K}{H} \approx -(1-\rho)s_L d\ln\frac{L}{H}$$

[50] See below for the derivation of the expression for s_L.

and so with a little more algebra we arrive at

$$d\ln(K/H) \approx \frac{(\rho-1)s_L(1-s_L)}{(\rho-\theta)s_K s_L + (\theta-1)(1-s_K)(1-s_L)} d\ln(L/H). \tag{18}$$

A similar log linearization can be used to obtain an expression for $d\ln(K/Y)$ starting from the expression for s_K, (17), above:

$$d\ln(K/Y) = d\ln s_K \approx -\left((1-s_L)\frac{s_K}{1-s_L}\rho d\ln\frac{K}{H} + s_L\rho d\ln\frac{L}{H}\right) + (\rho-\theta)\frac{s_K}{1-s_L}d\ln\frac{K}{H} + \theta d\ln\frac{K}{H}.$$

Simplifying this as $d\ln(K/Y) \approx \frac{-s_K(1-s_L)\rho+(\rho-\theta)s_K+(1-s_L)\theta}{1-s_L} d\ln\frac{K}{H} - s_L\rho d\ln\frac{L}{H}$ and substituting in (18), we have that $d\ln(K/Y) \approx \left(\frac{[-s_K(1-s_L)\rho+(\rho-\theta)s_K+(1-s_L)\theta](\rho-1)s_L}{(\rho-\theta)s_K s_L+(\theta-1)(1-s_K)(1-s_L)} - s_L\rho\right) d\ln\frac{L}{H}$ which, with some (painful) algebra, and multiplying a dividing by -1 to write it in terms of $d\ln(H/L)$, can be expressed as

$$d\ln(K/Y) \approx \frac{(\rho-\theta)(1-s_L-s_K)s_L}{(\theta-\rho)s_K s_L + (1-\theta)(1-s_L)(1-s_K)} d\ln(H/L) \tag{19}$$

Note the symmetry with the expression for the other nesting of capital, (13), above. In this expression, the denominator is always positive and so the response of capital intensity has the same sign as $\rho-\theta$.[51]

Now let us suppose we have an estimate of $\frac{d\ln(K/Y)}{d\ln(H/L)} = C$. We can use (19) to solve for θ as a function of C and the other parameters with the steps

$$C[(\theta-\rho)s_K s_L + (1-\theta)(1-s_L)(1-s_K)] = (\rho-\theta)(1-s_L-s_K)s_L,$$

so

$$(Cs_K s_L - C(1-s_L)(1-s_K) + (1-s_L-s_K)s_L)\,\theta = \rho(1-s_L-s_K)s_L + C\rho s_K s_L - C(1-s_L)(1-s_K),$$

which we can solve for

$$\theta = \frac{C\rho s_K s_L + \rho(1-s_L-s_K)s_L - C(1-s_L)(1-s_K)}{Cs_K s_L - C(1-s_L)(1-s_K) + (1-s_L-s_K)s_L},$$

and simplifying a little further allows us to arrive at our expression which we used to solve for θ

[51] As for the denominator being positive, note that holds if $(\rho-\theta)s_K s_L < (1-\theta)(1-s_L)(1-s_K) = (1-\theta)s_K s_L + (1-\theta)(1-s_K-s_L)$ so if $(\rho-1)s_K s_L < (1-\theta)(1-s_K-s_L)$, which always holds since $\rho, \theta < 1$.

in column (6) of Table 8 (which also implicitly uses the fact that, by definition $s_L = 1 - s_H - s_K$:

$$\theta = \frac{\rho(1 - s_L - s_K + Cs_K)s_L - C(1 - s_L)(1 - s_K)}{(1 - s_L - s_K)(s_L - C)} \tag{20}$$

With a little bit of algebra, one can show that in order for θ and ρ to be less than one as required, we will at least need that $s_L > C$.[52] As became evident in section 6, this may limit the plausibility of this parameterization in many cases.

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

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

and

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

This also gets us to expressions for the labor factor shares, in particular the

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

used above, and to relative wages

$$\frac{W_H}{W_L} = \frac{\alpha(1-\beta)}{(1-\alpha)}\left(\beta\left(\frac{K}{H}\right)^{\theta} + (1-\beta)\right)^{\rho/\theta-1}\left(\frac{H}{L}\right)^{\rho-1}. \tag{23}$$

This has the log differential form $d\ln(W_H/W_L) \approx (\rho - \theta)\frac{s_K}{1-s_L}d\ln(K/H) + (\rho - 1)d\ln(H/L)$. Substituting in for $d\ln(K/H)$ from (18) produces

$$\frac{d\ln(W_H/W_L)}{d\ln(H/L)} \approx \frac{(\rho-\theta)(1-\rho)s_L s_K}{(\rho-\theta)s_K s_L + (\theta-1)(1-s_K)(1-s_L)} + \rho - 1. \tag{24}$$

[52]Supposing $s_L > C$, it is required by (20) that $\rho(1 - s_L - s_K + Cs_K)s_L - C(1 - s_L)(1 - s_K) < (1 - s_L - s_K)(s_L - C)$ in order for $\theta < 1$. Rearranging, this requires that $(\rho - 1)(1 - s_L - s_K + Cs_K)s_L < 0$, which, since $\rho < 1$, holds only if $1 - s_L - s_K + Cs_K > 0$ so $s_H > -Cs_K$ (a non-demanding restriction at the values of C we estimate). Supposing $s_L < C$, in contrast, means $\theta < 1$ only if $s_H < -Cs_K$ which would only be allowable if C were negative, contradicting the supposition that $s_L < C$.

A.2 Derivation Model Version 2

For complete fastidiousness – even though it is largely symmetric and therefore redundant – this section executes the derivation for the alternative nesting. As before, begin with a rewritten version of (12):

$$Y = A\left(\alpha\left(\beta\left(\frac{K}{L}\right)^{\theta} + (1-\beta)\right)^{\rho/\theta} + (1-\alpha)\left(\frac{H}{L}\right)^{\rho}\right)^{1/\rho} L \tag{25}$$

which delivers our first order condition for capital,

$$r = A\left(\alpha\left(\beta\left(\frac{K}{L}\right)^{\theta} + (1-\beta)\right)^{\rho/\theta} + (1-\alpha)\left(\frac{H}{L}\right)^{\rho}\right)^{1/\rho-1} \alpha\left(\beta\left(\frac{K}{L}\right)^{\theta} + (1-\beta)\right)^{\rho/\theta-1} \beta\left(\frac{K}{L}\right)^{\theta-1} \tag{26}$$

Taking the log differential and setting it equal to zero, we have that,

$$0 \approx (1/\rho - 1)\left(s_K \rho d\ln\frac{K}{L} + s_H \rho d\ln\frac{H}{L}\right) + (\rho/\theta - 1)\frac{s_K}{1-s_H}\theta d\ln\frac{K}{L} + (\theta-1)d\ln\frac{K}{L},$$

which we can rewrite as

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

and rearranging terms we finally obtain

$$d\ln(K/L) = \frac{(\rho-1)(1-s_H)s_H}{(\rho-\theta)s_K s_H + (\theta-1)(1-s_K)(1-s_H)} d\ln(H/L), \tag{27}$$

which (after combining terms in the denominator) is very similar to (18). Notice that we only have to subtract $d\ln(H/L)$ from both sides of (27) to get an expression for $d\ln(K/H)$ and then we can take a weighted average of this and (27) to get how much capital per *worker*, $N = H + L$, (rather than low skill worker, L) changes with skill ratios,

$$d\ln(K/N) = \frac{(\rho-1)(1-s_H)s_H - \phi_h((\rho-\theta)s_K s_H + (\theta-1)(1-s_K)(1-s_H))}{(\rho-\theta)s_K s_H + (\theta-1)(1-s_K)(1-s_H)} d\ln(H/L) \tag{28}$$

(with $\phi_h = H/N$), which is the parametric analog of (3).

Now let us log differentiate s_K,

$$s_K = \left(\alpha\left(\beta\left(\frac{K}{L}\right)^{\theta} + (1-\beta)\right)^{\rho/\theta} + (1-\alpha)\left(\frac{H}{L}\right)^{\rho}\right)^{-1} \alpha\left(\beta\left(\frac{K}{L}\right)^{\theta} + (1-\beta)\right)^{\rho/\theta-1} \beta\left(\frac{K}{L}\right)^{\theta}, \tag{29}$$

which implies,

$$d\ln s_K \approx -\left(s_K\rho d\ln(K/L) + s_H\rho d\ln(H/L)\right) + (\rho-\theta)\frac{s_K}{1-s_H}\theta d\ln(K/L) + \theta d\ln(K/L)$$

and collecting the (K/L) terms,

$$d\ln s_K \approx \frac{(\rho-\theta)s_K - \rho s_K(1-s_H) + \theta(1-s_H)}{1-s_H} d\ln(K/L) - s_H\rho d\ln(H/L)$$

and substituting in (27) and using that $d\ln s_K = d\ln(K/Y)$, we have that,

$$d\ln(K/Y) \approx \left(\frac{[(\rho-\theta)s_K - \rho s_K(1-s_H) + \theta(1-s_H)](\rho-1)s_H}{(\rho-\theta)s_K s_H + (\theta-1)(1-s_K)(1-s_H)} - s_H\rho\right) d\ln(H/L).$$

With some algebra, this can be simplified as

$$d\ln(K/Y) \approx \frac{(\rho-\theta)s_H(1-s_H-s_K)}{(\rho-\theta)s_K s_H + (\theta-1)(1-s_K)(1-s_H)} d\ln(H/L), \tag{30}$$

which is exactly (13) (after multiplying the numerator and denominator by -1).

Now let us use this to solve for θ as a function of the other parameters, including $C = \frac{d\ln(K/Y)}{d\ln(H/L)}$. This means $C(\rho-\theta)s_K s_H + C(\theta-1)(1-s_K)(1-s_H) = (\rho-\theta)s_H(1-s_H-s_K)$. So we can collect the terms with a θ to get $\theta = \frac{-C\rho s_K s_H + C(1-s_K)(1-s_H) + \rho s_H(1-s_H-s_K)}{-Cs_K s_H + C(1-s_K)(1-s_H) + s_H(1-s_H-s_K)}$, which we'll simplify as

$$\theta = \frac{\rho(1-s_H-s_K-Cs_K)s_H + C(1-s_H)(1-s_K)}{(1-s_K-s_H)(C+s_H)}, \tag{31}$$

Parallelling (20) above, this expression requires that $s_H > -C$ (and $s_L > Cs_K$) in order for $\theta < 1$.

Notice that we can combine conditions (30) and (28), defining $C_1 = \frac{d\ln(K/N)}{d\ln(H/L)}$ and $C_2 = \frac{d\ln(K/Y)}{d\ln(H/L)}$, to solve for the vector (ρ, θ) as a function of $(C_1, C_2, s_K, s_H, \phi_h)$. The solution to this problem is described in the section A.3.

The first order conditions for both types of labor are

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

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

so relative wages are

$$\frac{W_H}{W_L}=\frac{1-\alpha}{\alpha(1-\beta)}\left(\beta\left(\frac{K}{L}\right)^{\theta}+(1-\beta)\right)^{1-\rho/\theta}\left(\frac{H}{L}\right)^{\rho-1}. \tag{32}$$

Taking the log differential of this expression we obtain

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

which, after substituting in (27), becomes

$$d\ln(W_H/W_L)\approx\left(\frac{(\theta-\rho)s_K(\rho-1)s_H}{(\rho-\theta)s_Ks_H+(\theta-1)(1-s_K)(1-s_H)}+(\rho-1)\right)d\ln(H/L) \tag{33}$$

which can be rearranged to the expression used in section 6, equation (14).

A.3 Joint estimation of ρ and θ

Now let us combine conditions (30) and (28) to solve for ρ and θ. Defining $C_1=\frac{d\ln(K/N)}{d\ln(H/L)}$ and $C_2=\frac{d\ln(K/Y)}{d\ln(H/L)}$, with some small rearrangement of terms we can get to:

$$[(\rho-1)s_Hs_K+(\theta-1)(1-s_H-s_K)]C_1=(\rho-1)s_H(1-s_H)-\phi_H[(\rho-1)s_Hs_K+(\theta-1)(1-s_H-s_K)]$$
$$[(\rho-1)s_Hs_K+(\theta-1)(1-s_H-s_K)]C_2=(\rho-\theta)s_H(1-s_H-s_K)$$

So now let us collect terms with ρ, θ, and everything else:

$$-(1-s_H)(1-s_K)(C_1+\phi_H)+s_H(1-s_H)=\rho s_H(1-s_H-(C_1+\phi_H)s_K)-\theta(\phi_H+C_1)(1-s_H-s_K)$$

and

$$-(1-s_H)(1-s_K)C_2=\rho s_H(1-s_H-s_K-C_2s_K)-\theta(s_H+C_2)(1-s_H-s_K)$$

Now substracting $\phi_H + C_1$ times the second equation from $s_H + C_2$ times the first equation, we can solve for ρ :

$$\rho = \frac{(s_H + C_2)[-(1-s_H)(1-s_K)(C_1+\phi_H) + s_H(1-s_H)] + (\phi_H + C_1)(1-s_H)(1-s_K)C_2}{s_H(s_H+C_2)(1-s_H-(C_1+\phi_H)s_K) - (\phi_H+C_1)s_H(1-s_H-s_K-C_2 s_K)}.$$

Simplifying we have

$$\rho = \frac{(s_H + C_2)(1-s_H) - (\phi_H + C_1)(1-s_H)(1-s_K)}{(s_H + C_2)(1-s_H) - (\phi_H + C_1)(1-s_H)(1-s_K)}. \tag{34}$$

Similarly, we can subtract $1 - s_H - (C_1 + \phi_H)s_K$ times the second equation from $1 - s_H - s_K - C_2 s_K$ times the first equation from the second equation to solve for θ:

$$\theta = \frac{(1-s_H-s_K(1+C_2))(1-s_H)[s_H - (1-s_K)(C_1+\phi_H)] + (1-s_H-(C_1+\phi_H)s_K) * (1-s_H)(1-s_K)C_2}{-(1-s_H-s_K-C_2 s_K)(\phi_H+C_1)(1-s_H-s_K) + (1-s_H-(C_1+\phi_H)s_K)(s_H+C_2)(1-s_H-s_K)}$$

Simplifying

$$\theta = \frac{(1-s_H-s_K)(1-s_H)[(s_H+C_2) - (\phi_H+C_1)(1-s_K)]}{(1-s_H-s_K)(1-s_H)[(s_H+C_2) - (\phi_H+C_1)(1-s_K)]}. \tag{35}$$

Notice, for example, that if capital output ratios are unaffected by skill mix (so $C_2 = 0$), equations (34) and (35) reduce to

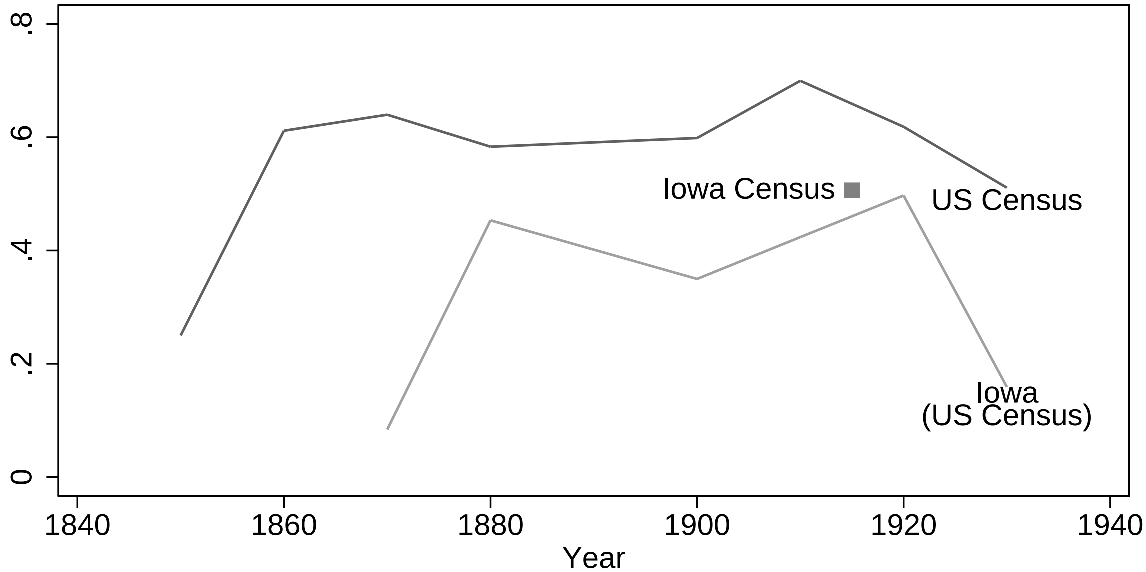
$$\rho = \theta = \frac{s_H(1-s_H) - (1-s_H)(1-s_K)(C_1+\phi_H)}{s_H(1-s_H-(C_1+\phi_H)s_K) - (\phi_H+C_1)(1-s_H-s_K)}$$

Our empirical analysis produces estimates of C_1 and C_2 which we want to translate into estimates of ρ and θ using these equations. For this, we will also need reasonable values of the share parameters that make up the rest of the terms in the equations. Let us start with a baseline assumption that 50% percent of manufacturing workers were skilled, so we will set $\phi_H = 0.5$.[53] Absent better information we also assume $s_K = 0.3$, making overall labor share 0.7. (CITATIONS) To break this into the cost shares of skilled and unskilled labor, we need more than just ϕ_H, we also need information on the relative wages of skilled and unskilled workers. To the best of our ability to measure it, the "return" to literacy, that is $ln(w_H/w_L)$ appears to be 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

[53]The share of manufacturing workers that were literate was considerably higher than this. However, it is likely that not everyone who self-reported literacy could be hired into skilled jobs in manufacturing. We consider simulations with other values of ϕ_H as well. (SEE ALSO GOLDIN OCCUPATIONAL DEFINITION)

age 20.[54] Figure A1 shows our estimates of the return to literacy by year.[55]

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.

Now if $\phi_H = 0.5$ and $ln(w_H/w_L) = 0.5$, it implies that $H/L = 1$, which means that the relative wage bills $\frac{H}{L}\frac{w_H}{w_L} = e^{0.5} = 1.65$. Given this, high-skill labor should be a little less than 2/3 of the wage bill and therefore about 45% of total costs $(2/3 * 0.7)$. So we set at baseline $s_H = 0.45$ and $s_L = 0.25$.

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

[55] 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.