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

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Abstract

This paper estimates the elasticity of substitution between capital and skill in manufacturing using immigration-induced variation in skill-mix across U.S. counties between 1860 and 1930. We find evidence consistent with a pattern where capital initially complemented both skilled –literate– and unskilled labor, and, unlike today, was more complementary with unskilled labor. Around 1890 capital increased its relative complementary with skilled labor. Simulations calibrated to our estimates imply the level of capital-skill complementarity after 1890 likely allowed the manufacturing sector to absorb the large wave of eastern and southern European migrants with only a modest decline in less-skilled relative wages. This would not have been possible under the older production technology.

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The recent recession and persistently rising inequality in the U.S. are once again raising concerns that technological change is outpacing many workers' ability to adapt to it (Brynjolfsson and McAffee, 2011). These concerns echo with stunning similarity to those of earlier times of disruption, including the Great Depression (e.g., Jerome, 1934; Keynes, 2008) and industrialization (e.g., Marx, 1932).[1] 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). In this view, capital's greater complementarity with the most skilled workers (compared to middle- or less-skilled workers) combined with the falling relative cost of capital (which embodies much of technological change), have pushed up relative demand for skill (See also Krusell, Ohanian, Rios-Rull and Violante., 2000).[2] In modern times this is thought to be due to advances in computers (e.g., Autor, Levy and Murnane, 2003), but before computers, 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] A body of indirect or correlational evidence, however, suggests that in the nineteenth century, capital in manufacturing instead tended to push up demand for the least skilled workers (e.g., Atack, Bateman and Margo, 2004; James and Skinner, 1985). Industrialization brought production which was both more unskilled-intensive and capital-intensive than the "artisanal" production it pushed out (e.g., Goldin and Sokoloff, 1984).[4]

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 Second Industrial Revolution, starting in the mid-nineteenth century and finishing at the outset of the Great Depression. Following most of the literature on technology and firms during the period we study, we focus solely on the manufacturing sector.[5] The first aim of this paper is to provide more credible, direct evidence of the level of complementarity between capital and skills and how it changed. To identify this, we exploit the effect that large waves of immigration (and, implicitly, immigration

[1]For a recent view on this issue see "The Future of Jobs: The Onrushing Wave," *The Economist*, January 2014. See Mokyr, Vickers and Ziebarth (2015) for a recent review about "technological anxiety" with a historical perspective on economists' views about the relation (race) between technology and workers, and Chui, Manyika and Miremadi (2016) for a business perspective on the opportunities for automation and challenges arising from technological advances.

[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 largely glossing over the more nuanced 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). We return to this later.

[4]This change may not, however, have been entirely "de-skilling," as artisans may have been less "skilled" (lower paid) than the white collar workers that also rose with factory production (Katz and Margo, 2013). This so-called polarization is further discussed below. Katz and Margo (2013) also show, however, that more capital intensive factories in 1880 had an overall higher unskilled labor share (Table 3, panel B), perhaps in part because white collar work was still a small share of manufacturing employment then.

[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.

restrictions) in the nineteenth and early twentieth century had on each urban U.S. county's skill mix, and ask how capital intensity of the industries in those areas responded, akin to Lewis (2011) and Lafortune, Tessada and Gonzalez-Velosa (2013) approaches.[6] We do not rely on actual regional patterns of immigration, but instead use an "ethnic enclave" or "shift-share" style instrumental variable strategy which imputes the impact of immigration on skill mix by apportioning national arrivals, by origin, to their ethnic enclaves in a base year. The idea behind this instrument is that enclaves attract new migrants from the same source because of the desire to settle in a culturally familiar environment (or family ties). In particular, this approach does *not* assume immigrants were unresponsive to demand conditions (historical evidence suggests they were, e.g., Rosenbloom, 2002), but rather that local relative demand shocks are not so highly correlated over time that ethnic enclaves develop in anticipation of relative skill mix demand decades later.[7] This approach has been used successfully in modern immigration research (e.g., Card, 2001; Cortés, 2008), but until recently, has seen little application in historical data (though see Goldin, 1994).

In addition to being a paper about technology, this is also a paper about immigration. Our second aim is to gain insight into how much relative wages in the manufacturing sector would have needed to change to adapt to the large waves of immigration during this era. In theory, the impact 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).[8] Whether this makes any difference at realistic parameter values, however, has not really been evaluated. In this paper we are examining an era in which production tradeoffs may have been quite different from modern times, even while concerns about the impact of technological change and immigration were quite similar, motivating our interest.

We measure skill using literacy, which observed at the county level from tabulated Censuses of Population data. Its key advantage is that it is a pre-labor market skill metric (and in fact, it is the only pre-labor metric widely available prior to 1940). The other main option in this era are occupational based definitions of skills, which we believe are more likely to reflect demand conditions. The downside of using literacy, however – a binary skill metric – is it that it does not allow us to test for more subtle interactions between capital and skills (of the sort that would lead to "polarization," per Gray, 2013; Katz and Margo, 2013). Nevertheless, literacy rates appear

[6] Griliches (1969) was the first to use regional differences in skill mix to identify capital-skill complementarity.

[7] While immigrants likely do choose destinations in anticipation of the path of future skill demands to some degree – and hence the instrument may not represent a "pure" supply shock – it seems plausible that the instrument is much more strongly weighted towards supply than are observed changes in skill mix (OLS estimates). Furthermore, while we are not aware of any evidence of the autocorrelation of local demand shocks in this era, analysis of the modern U.S. suggests local demand shocks may not persist much beyond a decade (Blanchard and Katz, 1992), the minimum lag which our enclave measure is entered into the instrument.

[8] Similarly, 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 reflect skill rankings captured by occupations.[9] Furthermore, this is of concern mainly if the changing relationship we observe between skills and capital is driven by shifts in the occupation mix by literacy; in simulations, we have been unable to account for our findings in this way.

Our outcomes come from industry x city (or county) tabulations of the Census of Manufacturing from 1860 to 1930, which we digitized. We first use them estimate the aggregate response of capital intensity to a change in the skill ratio, which we allow to differ in the first and second half of this period. We also estimate responses *within* detailed industries, by controlling for unrestricted industry-specific trends in capital intensity, in order to assess how much the aggregate results are confounded by shifts in industry mix.[10]

This brings us to our findings. Our instrumental variables estimates suggest that (predicted) immigration had a significant impact on skill ratios –literacy rates– in local labor markets.[11] Furthermore, aggregate capital intensity responded differently in the nineteenth and twentieth century to similar skill mix shocks. Between 1860-1880, capital's response was consistent with it being a q-complement of both skilled and unskilled labor, and, unlike today, the complementarity was stronger with *unskilled* labor, largely supporting the "deskilling" view of nineteenth century manufacturing. This changed dramatically during the period 1890-1930, when capital became relatively more complementary with skilled labor and a q-substitute for unskilled labor (more like today, and consistent with Goldin and Katz, 1998).

Shifts in industry mix have limited influence on both sets of responses, though the rich set of industry controls can make the estimates statistically insignificant.[12] Despite the fact that we find that immigration induced within-industry changes in skill ratios, simulations of a parametric production function calibrated to our estimates suggest that the manufacturing sector could have absorbed the massive early twentieth century immigration wave with comparatively modest changes in relative wages. Specifically, our calibration suggests that absorbing the entire flow of illiterate immigrants arriving after 1897 required a 7% decline in less-skilled relative wages in manufacturing, allowed for by a slower increase in the sector's capital intensity. In contrast, under nineteenth century technology parameters, which lacked the same capital substitution

[9]Figure 1 shows, for example, that literacy rates are monotonic in the manufacturing occupational ranking used in Katz and Margo (2013) throughout our sample period, with the least skilled common laborers in manufacturing always distinctly less literate than both artisans or white collar workers.

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

[11]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 (as suggested by Rosenbloom, 2002)– our approach would not be feasible.

[12]The minor role for industry mix responses in manufacturing reinforces that the significant response of industry mix in the agriculture sector to immigration during this same period (Lafortune et al., 2013) may be due to the lack of specificity of capital in agriculture, rather than something else about this period.

possibilities, absorbing the same immigration wave would have required pushing down less-skilled relative wages severely, perhaps as much as 35%. In short, production technology played a central role in the U.S. economy's ability to absorb this large wave of immigrants.

1 Historical 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 arrival of skilled British and other European artisans in the nineteenth century, and finally to arrival of the masses of less-skilled 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).[13] 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 weak labor market (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 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 the Northern U.S. in the mid-nineteenth century, which is why the North industrialized first (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 have pushed producers towards adopting more labor-intensive methods (e.g., p. 87). Kim (2007) shows that in 1850-1880, U.S. counties with higher immigrant density had larger manufacturing establishments. At the same time, Chandler (1977) argues that modern manufacturing required professional management, and you also see

[13]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".

evidence of a shift to more "white collar" jobs in the late nineteenth century (Katz and Margo, 2013).

After the switch from an artisanal production to a factory system manufacturing is thought to have begun a switch to a continuous production systems that increasingly relied on electricity and (more recently, automated) machinery. This process that started around the turn of the century is what Jerome called "mechanization".[14] The exact timing may have differed by industry, and of particular interest to us, location.[15] Goldin and Katz (1998) argue and provide evidence that the latter change is associated with greater skill and capital requirements, and so 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 embraced electricity more than others saw a relatively larger increase in the employment of non-production workers, but found decreases in the proportion of jobs requiring "dexterity" (mostly skilled craftsman), relative to those requiring manual labor among production workers. 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.

In an earlier era, Goldin and Katz (1998) argue that factory output likely substituted for the less capital-intensive artisanal production. This is a sensible view, but it is only directly supported by a solitary study: James and Skinner (1985). They show that in 1850 capital and labor were more substitutable in manufacturing sectors that were more skill-intensive than in sectors that were less skill-intensive. The paper does not describe how the skill intensity of the sectors was assessed.

Many of the studies above use variation in some capital-use measure –the right-hand side variable– to estimate the response of skill mix measures. We examine the other side of the coin: how immigration-induced changes in skill mix are associated with adjustments in various measures of capital use. Like the twin motivations for Jerome's study, both approaches should reveal the nature of the complementarity between capital and skills (demonstrated below). Our approach will also give insight into the ability of the economy to "absorb" large immigrant inflows, as adjustments to technology can help mitigate the impact of immigration on the wages

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

[15] 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.

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

2 Theoretical Framework

Our work starts from a simple framework that considers a single (aggregate) production function with three production factors: capital (K), high-skilled labor (H) and low-skilled labor (L), which is a common formulation both in the immigration and the technology adoption literature (see for example Lewis, 2011, 2013). So let $Y = g(H, L, K)$, where Y is aggregate output.[16] 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. Wage levels are determined at the local economy level but since they are not observed in our data, we will focus on factor ratios which are observed, since these will determine wages in equilibria.

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

[16] 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.

returns to scale, this translates into,[17]

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

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-skill workers on the capital-to-low-skill labor ratio:

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

The denominator in equation (2) is positive if the production function displays decreasing returns to capital, which was assumed. Therefore, the sign of the numerator indicates input complementarity with high-skill labor: capital and high-skill labor are "q-complements" if $\frac{\partial^2 Y}{\partial K \partial H} > 0$ and "q-substitutes" if $\frac{\partial^2 Y}{\partial K \partial H} < 0$. One can also subtract $d \ln H$ from both sides to derive a symmetric expression for the complementarity between capital and low-skill labor from the response of the capital-to-high-skill labor ratio to changes in the relative endowment of high-skill workers. The problem with this approach 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-skill labor 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:

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

Note that the relationship between K/N and H/L is not dispositive, on its own, of the level of complementarity between capital and either type of labor. However, comparing it with ϕ_H indicates whether capital and high-skill labor are complementary or substitutes and the relative degree of that relationship compared to that of low-skill workers.

We can also obtain similar information simply by evaluating the response of the capital-

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

output ratio, given by:

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

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

The relationship of capital intensity to skill ratios is important in understanding how changes in capital affect relative skill demand. This can be seen explicitly by rewriting (4) as

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

The numerator of (5) contains the response of high-skill relative wages (with $W_H = \partial Y/\partial H$ and $W_L = \partial Y/\partial L$), assumes 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.[18] (5) is an explicit reminder for 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 measures of the wage structure are quite crude during this era.

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

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

where $\frac{\partial \ln(W_H/W_L)}{\partial \ln(L/H)}$ represents the short-run (capital fixed) relative wage adjustment to a change in relative skill supply, which is negative. Note that this expression implies that the long-run relative wage impacts of a change in skill ratios (say, induced by immigration) may be smaller or larger than this depending on the relative complementarity of capital with skill. If capital complements skilled labor relative to unskilled labor – if the response in (5) is positive, so that $\frac{\partial \ln(W_H/W_L)}{\partial \ln K} > 0$ and $\frac{\partial \ln K}{\partial \ln(H/L)} > 0$ – then the long-run response of relative wages to immigration is diminished by the adjustment of capital.[19] Relative wage impacts are larger than this when capital is skill-

[18] Indeed, as we will describe again in Section 5, a positive response to capital of the marginal product of skilled labor that is larger in proportional terms than the response of unskilled labor is often what is called "capital-skill complementarity" (e.g., Krusell et al., 2000). We will instead attempt to describe this more precisely by saying "capital is a (q-)complement of skilled labor relative to unskilled labor."

[19] While for this to be true it is necessary that capital be not just a relative, but an absolute complement of skill –

neutral. Two specific contrasting examples of prominently used production functions may be helpful in delineating this point. It is common for studies of the modern-day labor market impact of immigration to model labor demand using a constant elasticity of substitution (CES) production function featuring separable capital, like $K^{\gamma}\left(H^{\frac{\sigma-1}{\sigma}}+L^{\frac{\sigma-1}{\sigma}}\right)^{\frac{(1-\gamma)\sigma}{\sigma-1}}$. In such a setup, capital's share is fixed at γ and

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

Put differently, the response of relative wages to relative supply estimates of the inverse elasticity of substitution between H and L which, more to 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 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.

Alternative Models Empirically, apparent shifts in capital intensity are potentially confounded by endogenous shifts in the industry mix predicted by simple open economy models (so-called "Rybczynski effects"). With one historical exception (Lafortune et al., 2013), these have generally been found to be small in response to immigration-induced skill mix shocks (e.g., Card and Lewis, 2007; Gonzales and Ortega, 2011; Lewis, 2003). The primary way in which we will address this is with industry controls, a key motivation for our data collection.

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. In this era, this might be represented by a shift between "artisanal" and "factory" production. Since the latter is thought to be more capital-intensive, this potentially also confounds our estimates. Researchers typically proxy for factor production with plant size (e.g., Kim, 2007), therefore we will also study plant size as an outcome (in the appendix).

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.

3 Empirical Methodology

3.1 Baseline equation

Following the results from our model, we begin by estimating this equation (for $J = N, Y$):

$$\ln\left(\frac{K}{J}\right)_{ct} = \gamma_{\text{early}} \ln\left(\frac{H}{L}\right)_{ct} \times \mathbb{1}\left(t \in \{\text{early}\}\right) + \gamma_{\text{late}} \ln\left(\frac{H}{L}\right)_{ct} \times \mathbb{1}\left(t \in \{\text{late}\}\right) \\ + \nu_c \times \mathbb{1}\left(t \in \{\text{early}\}\right) + \delta_c \times \mathbb{1}\left(t \in \{\text{late}\}\right) + \eta_t + \epsilon_{ct} \tag{8}$$

where $(K/J)_{ct}$ corresponds to either the capital per worker (K/N) or the capital-output ratio (K/Y) in county c at time t, $(H/L)_{ct}$ is the high-to-low-skilled labor ratio in the county c at time t, $\mathbb{1}\left(t \in \{early\}\right)$ and $\mathbb{1}\left(t \in \{late\}\right)$ are, respectively, indicators for the first and second half of our sample period (defined below); ν_c and δ_c represent county and η_t time effects, respectively. Standard errors will be calculated to be robust to arbitrary error correlation within county and regressions are unweighted.

Since our interest lies in comparing the evolution of the production function over our sample, we divide it between an early period and a late period, allowing γ to change between the two. We unfortunately do not have sufficient variation to reliably estimate γ separately by decade, though we can estimate it with as few as two decades. So what we do instead is move the cut-off points between an early and earlylate period to attempt to identify when, if any, changes seem to have occurred in the relationship we attempt to estimate. Since historical analyses by Chandler (1977) and Jerome (1934) argue that the Second Industrial Revolution transformed the productive process of manufacturing, we will look for a change around the 1880-1890 period, years during which some of the elements of the Second Industrial Revolution took place.

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

This specification is motivated in part by Goldin and Katz (1998)'s argument that capital-skill complementarity arises across sectors (in their model, across the combination of a machine- and goods-producing sectors): it examines how manufacturing's capital intensity in the county as whole adjusts to the changes in the skill-mix of workers. Estimates of (8) may alternatively be viewed as suffering from aggregation bias: shifts in output mix towards industries that use a different production technology could confound the results. This is why we also collected industry-county data, which allow us to estimate responses within industry as well:

$$\ln\left(\frac{K}{J}\right)_{cit} = \gamma_{\text{early}} \ln\left(\frac{H}{L}\right)_{ct} \times \mathbb{1}\left(t \in \{\text{early}\}\right) + \gamma_{\text{late}} \ln\left(\frac{H}{L}\right)_{ct} \times \mathbb{1}\left(t \in \{\text{late}\}\right) \\ + \nu_c \times \mathbb{1}\left(t \in \{\text{early}\}\right) + \delta_c \times \mathbb{1}\left(t \in \{\text{late}\}\right) + \eta_t + \mu_{it} + \epsilon_{cit} \tag{9}$$

In this specification, the outcome, $\left(\frac{K}{J}\right)_{cit}$, varies additionally at the industry, i, level, and the specification includes controls for unrestricted trends in aggregate capital intensity by industry, μ_{it}.[20] Estimates of (9) and (8) will differ only if there are systematic industrial composition shifts that occurred in response to changes in factor endowments. In the appendix, we also test this directly by using as an outcome variable the share of labor in industries that use some factors more intensively. Standard errors will again be calculated to be robust to arbitrary error correlation within each county.[21]

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 compensated for. Thus, depending on how our outcomes are correlated with relative wages, we could be over or under-estimating the relationship between our variables of interest. Furthermore, it is important to note that manufacturing is only one sector in the broad economy – a minority of employment – so local demand shocks outside manufacturing could be an important source of endogeneity.[22] It is thus difficult to sign exactly the bias of the basic correlations. OLS estimates might also be attenuated by error in the measurement of skill ratios due to sample variation.[23]

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

[20] In theory it is possible to also control for industry x county effects, but since the right hand side does not vary at this level, in practice it does not affect the estimates to do so.

[21] To mimic the equal county weighting of (8), we weigh (9) by the inverse number of industries in each county x year.

[22] According to the Census of Population, it ranges from roughly one quarter to one third of employment in identified cities over the years in our sample, using industry codes constructed by Ruggles, Alexander, Genadek, Goeken, Schroeder and Sobek (2010).

[23] 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.

patterns, would have on skill ratios. Specifically, the instrument is given by:

$$\ln(\widehat{H/L})_{ct} = \ln\left(\frac{\widehat{H_{ct}^{nat}} + \sum_j \left(\frac{N_{jc0}^{imm}}{N_{j0}^{imm}}\right) H_{jt}^{imm}}{\widehat{L_{ct}^{nat}} + \sum_j \left(\frac{N_{jc0}^{imm}}{N_{j0}^{imm}}\right) L_{jt}^{imm}}\right) \tag{10}$$

where $\widehat{H_{ct}^{nat}}$ and $\widehat{L_{ct}^{nat}}$, represent, respectively, the *predicted* (defined below) stock of native-born high- and low-skill workers in (US) county c and year t; N_j^{imm} is the stock of foreign-born individuals (not broken out by skill) born in j; H_{jt}^{imm} and L_{jt}^{imm} are the *national* stocks of high-skill and low-skill individuals from each country j in each period t, respectively. Note that the numerator and denominator includes $\frac{N_{jc0}^{imm}}{N_{j0}^{imm}}$, which represents the share of individuals from j living in c in some base year. This is used to apportion the current stocks of immigrants by country to locations within the U.S. Thus, the instrument represents the ratio in the number of high- and low-skill individuals, respectively, that would be living in c if immigrants were apportioned across counties (by origin) 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; Cortés, 2008; Lewis, 2011) but until recently has seen limited application in this historical context. It attempts to circumvent the problem of endogenous location choice by allocating individuals to counties based on the location of immigrants from one's country of birth in previous waves (and, for natives, by one's state of birth, as we will see below). 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 regionally (at least within the North) or even internationally (within 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 immigrants' origin mix shifted substantially in the late nineteenth century, we will use two base years: 1850 for 1860-1880 and 1880 for 1890-1930.[24]

If (10) includes only immigrants it does quite a good job of predicting immigrant skill ratios. However, as we are predicting proportional total changes in skill ratios, we need to normalize it by some defensibly exogenous measure of the skill ratio of natives in the area. Generally, this issue is not given much attention by researchers using this style of instrument –for example,

[24] While we could use a rolling basis approach, we elected to stick to two years since these correspond to the only two years in which 100 percent counts can be employed.

the predicted skill ratio is often just divided by the lagged observed skill mix, which might be endogenous– an exception to this is Smith (2012). The approach we settled on was to apportion natives to each county in a similar fashion as immigrants, using the stock of all natives (irrespective of their skills) in that year. However, if we just allocated natives by their observed distribution across counties (in other words, if we just defined $\widehat{H_{ct}^{nat}} = H_t^{nat} * N_{ct}^{nat} / N_t^{nat}$) we may be concerned that the distribution of natives across locations might be an endogenous response to local demand conditions. To correct for this, we allocate natives imposing fixed migration patterns from different states of birth to different counties measured in the same base year. Formally, for natives, our predicted number of high-skill natives in a county c at time t is given by

$$\widehat{H_{ct}^{nat}} = H_t^{nat} * \frac{\sum_s \frac{N_{cs0}^{nat}}{N_{s0}^{nat}} N_{st}^{nat}}{N_t^{nat}}$$

where s denotes the state of birth (with a similar expression for predicted low-skill natives, $\widehat{L_{ct}^{nat}}$). Thus, we allocate a fraction of all high-skill natives in the US at time t to county c depending on the share of the US native-born population that is predicted to be living in that county at that particular time. Another approach we tried was similar to Smith (2012): we used the base year ratio of high- and low-skill natives interacted with the national growth rate of skills among native-born workers. Thus, that version of the instrument represented the predicted skill ratio given the initial locations of immigrants and natives and *national* changes in the country mix of immigrants and the skill mix of immigrants and natives. Similar results were obtained and are available upon request.

This instrument will be valid unless past migrants selected their location based on how they anticipated the manufacturing sector to evolve *and* that later national flows of immigrants *by skill levels* were altered in response to those anticipated shocks. It is not invalidated if a location was particularly attractive to immigrants and also had a large change in its manufacturing sector, since we will include county fixed effects. It is also not invalidated if immigrants of a given skill level start arriving to the United States when the demand for their skill is highest, since we include time fixed effects. The identification strategy is compromised if, for example, German migrants settled in locations where they anticipate that the manufacturing sector will be demanding high-skill workers in the future and then, when the industry does so, relay the information back to Germany and in response to this, more German high-skill workers would arrive to the United States. However, for that to be a substantial concern, there must be a significant concentration of individuals of a given country of origin in one single location. Otherwise, each location would experience a different shock which would lead to a different evolution in the demands for skills from migrants back home. In the historical context we study, few counties include a very large fraction of immigrants from a given country. It is thus difficult to imagine that the increase in the number of immigrants in a given skill group, from a given country being driven by the higher demand for that skill in one or two counties.[25] Also, our strategy would be invalidated if immigrants located in cities where they anticipated that their skills were going to become more valuable in the future. We attenuate this concern 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. 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.

Nevertheless, we acknowledge that our instrument could still suffer from some biases. In that case, the comparison with the OLS will allow us to evaluate in what direction a more perfect instrument may lead us since we believe our instrument would, if anything, be biased in the same direction as the endogenous variable.

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. Given 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 for each decade from IPUMS data (Ruggles et al., 2010) from 1860 to 1930 (except in 1890, which are estimated from 100% tabulations in U.S. Department of Interior, United States Census Office, 1897, –see C.4 in the Data Appendix). There are really two options for defining "skill" in this data: occupation or literacy.[26] An advantage of literacy is that it is something close to a pre-labor market skill, whereas occupation-derived measures are a match between workers' skills and local labor market demand conditions. Furthermore, literacy is available uniformly during the period. It also correlates relatively well with the distinction of production and non-production workers where literacy would have been essential for the second type of employment but not for the first. 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. For example, Figure 2 shows the fraction of total US population that were immigrants by literacy. By the twentieth century, immigrants represented almost 50

[25] One potential exception is New York City, which was a top destination for many immigrant groups. In any case our results are not sensitive to dropping New York.

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

percent of all illiterate US based individuals. Finally, we have found a very high correlation between the literacy rate of immigrants in the US and the primary enrollment rates or literacy rates in the sending country, suggesting that the variation across groups stems not from selection but from different conditions before leaving for the United States.

The biggest concern one may have about using literacy is whether the changing relationship we document with capital could stem from changes within each literacy category. For example, Katz and Margo (2013) argue that there was polarization over this period leading to a lower share of workers in the middle of the occupational scale while Gray (2013) argues that electrification led to a hollowing out of the skill distribution in the manufacturing sector. While we think that this an important element to consider, we think that our simpler measure of skill is unlikely to mask too much heterogeneity. First, as shown in Figure 1, the divisions by occupational groups as done by Katz and Margo (2013) match monotonically our definition of literacy. Furthermore, we will argue that given the changes in literacy rates within each of these categories and the changes in shares of workers pertaining to each of these categories, our results are very unlikely to be due to "aggregation bias".

Recall that we use predicted immigration as a shock to local skill mix over the period 1860 to 1930. This is a period of great potential for this purpose as immigration flows were very large. It also includes periods of slower immigration driven by potentially exogenous factors (Civil War, First World War) and by a dramatic change in the legal environment (1924's Johnson Act). To construct this instrument, we require a reliable estimate of the location of immigrants of different origins in a "base year" (the N_{jc0}/N_{j0} in (10)). We use two different base years, 1850 and 1880, in part because both have 100% samples available from IPUMS (Ruggles et al., 2010). We use these 100% tables to alleviate concerns of small-cell biases (see Aydemir and Borjas, 2010). We also need to obtain the national stock of immigrants from each country by country/state of birth and skill. In principle, there are several ways we could have constructed the national number of high- and low-skill immigrants arriving after 1850. To be as consistent as possible, we chose to measure them with the stocks from each country (and U.S. state) in each decade between 1860 and 1930 by aggregating IPUMS data. The 1890 data had to again be constructed from tabulations, and in some cases by interpolating between 1880 and 1900 data (see Data Appendix).

Our outcome variables focus on the adjustment mechanisms in the manufacturing sector over this period. Our estimation framework calls for data at the level of the labor market x industry. These can be obtained from published Manufacturing Census tabulations. Conveniently for our analysis, manufacturing censuses occurred roughly concurrently with the Census of Population over this entire period. They are available in published tabulations which we have have digitalized.[27]

One issue in covering such a long time series is that the unit of geography reported in these

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

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 only available by county while in 1880 and later, the main geographic tabulations are for the largest cities, occasionally supplemented by tabulations for selected urban counties. Due to 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.[28]

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.[29] 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.[30]

While we obtained measures for a variety of outcomes, here we focus on capital, labor and output, which are the ingredients of our theoretical framework. Value of products and costs are available for the full period, which allows us to define value-added as our measure of output (Y). To measure labor (N), we use the measure of all workers. Value of capital, our key variable, is only available from 1860 to 1920. However, in 1910, 1920 and 1930, we have a measure of horsepower which we use to obtain a proxy measure of capital for 1930 based on the relationship between horsepower and capital in the two previous decades.[31] Since this measure of capital includes all forms of capital (land, buildings, machinery and equipment), we may also wish to look at a measure that focuses a bit more directly on machines instead of land. We first use horsepower directly. As we discussed before, this variable is available for 1910-1930. Before 1910, we impute horsepower from machinery capital for 1890 and 1900, which is separately reported in these two years.[32] Before 1890, neither horsepower nor machinery is separately tabulated, but from the sample data of Atack and Bateman (1999), we were able to find evidence that very few firms had positive horsepower in 1860. We thus replace our measure of horsepower with 0.1 for 1860 for all industries and counties.[33] Finally, capital utilization may also respond to skill ratios, so we use expenditure on fuel and rent of power (in some years it is a single category while in others, it was decomposed) as an alternative measure of capital which may

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

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

[30]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.

[31]$\widehat{ln(K)} = 0.77839346 ln(Horsepower)$ – see data Appendix.

[32]The estimated relationship from state-level tabulations is $\widehat{Horsepower} = 0.004 * M\&ECapital$ –see Data Appendix.

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

capture more utilization than purchase of capital. Again, since that variable is only available from 1890 onwards, we used micro-data from Atack and Bateman (1999) to determine that few firms devoted large amounts to fuel and power in 1860 and we thus proxy it with 0.1 for all industries and counties in that year.

We use IPUMS data to estimate $\phi_H = 0.85$, the fraction of workers in manufacturing that were literate. In order to interpret our estimates it is useful to know illiterate and literate workers' share of production costs, denoted s_L and s_H, respectively, in the model above. While we do not observe wages by literacy directly in manufacturing data, from 1890 onwards we can observe the wage bills of wage earners and salaried officials, also often described as "production" and "non-production" workers, as in Goldin and Katz (1998). We use the output share of wages by production worker status to impute output shares by literacy, s_L and s_H, by apportioning the shares of production and non-production workers who are literate in IPUMS data.[34] This is likely a lower-bound estimate of s_H since it is calculated assuming no return to literacy within production or non-production workers. We obtain estimates of $s_L = 0.0787$ and $s_H = 0.5085$, implying that the capital share was around 40 percent, consistent with Taylor and Williamson (1997).

We restrict our sample of analysis to any county that was included in Census of Manufactures tabulations over this period in at least three different years. In the aggregate analysis, we include all industries for a given city/county. In the industry by area analysis, we exclude the residual "All other industries" cells, as they are not comparable across years or areas and also exclude industry-year cells where the industry appeared in no more than 2 areas in that year.[35] Merged all together, we obtain a very rich panel including 37,278 industry-city-year observations. This includes a total 175 areas (more in some years than in others) and 137 industries (our classification over time generated 150 separate industries but 13 of them were eliminated due to the fact that they had too few observations in a given year –see Data Appendix for a list). These areas cover, on average, 58 percent of the U.S. immigrant population, and the industry division is very detailed.

The means of our sample are shown in Table 1 in which we present the two different distinctions we will make between early and late period. In the first panel, we call early 1860-1880 and the rest as late. In the second panel, we move our window by 10 years, implying that all

[34] For example, literate output share is calculated as

$$s_H = \frac{Hw_H}{Y} = \frac{Prod * w_{prod} * LitProd/Prod}{Y} + \frac{Non-prod * w_{non-prod} * LitNon-prod/Non-prod}{Y}$$
$$= s_{prod} * \frac{LitProd}{Prod} + s_{non-prod} \frac{LitNon-prod}{Non-prod},$$

where s_{prod} and $s_{non-prod}$ are the output shares of production and non-production workers' wages in the manufacturing data, respectively, which are multiplied by the literacy rates for production ($\frac{LitProd}{Prod}$) and non-production ($\frac{LitNon-Prod}{Non-prod}$) workers, obtained from IPUMS data.

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

observations from the 19th century are called early. What we can observe is that there is capital deepening over the full period, as can be seen from the change in values as we alter the cut-off points. Literacy in the US was also relatively high over this period, with the logarithm of skilled per unskilled worker of around two in the nineteenth century (around 80 percent literate), growing to about three in the early twentieth century (95 percent literate).

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 has seen a lot of use in modern studies of the labor market impact of immigration. To demonstrate visually how the instrument functions, we present, in Figure 3, the actual and instrumented skill ratio for two cities in our sample: Chicago and New Orleans. Chicago was particularly receiving immigrants of German origin and New Orleans, of Italian and Russian origins. Since German immigrants were very highly literate but their flow stopped by about 1910, Chicago is predicted to have first an increase in its literacy rate and then a slowdown by the later part of our sample. New Orleans, on the other hand, received migrants that had lower levels of literacy, particularly after 1880, and thus are predicted to decrease its skill ratio right until immigration slows down in the 1920s. The predictions generated by our instruments are indicative of the trends we find in the actual data.

Appendix Table B.1 shows the first stage regressions estimated in the industry x county level data combining all years of data. To account for both the fact there are multiple "copies" of a county within a year and for the fact that the errors are likely autocorrelated over time, we cluster standard errors by county. In addition, we weigh by the inverse of the number of industries represented in a county (to give each county equal weight).[36] As we move from column (1) to (3), we explore increasingly demanding controls for industry, which will parallel our analysis below: with no industry effects, with industry effects, and with industry x year effects. In Appendix Table B.1, the only reason they should make any difference is because of small changes in the composition of areas which identify the relationship (since the instrument and skill mix measure do not vary by industry). These added controls have little effect on the first stage, which remains highly significant and almost unmoved in terms of magnitude. The results suggest that a change of 1 percent in our predicted skill ratio translates to about a 0.70 percent change in the actual skill ratio of a county, if we split the sample at 1880, and about about 0.95 percent if we split it at 1890. The fact that it is less than one could be consistent with an endogenous location choice by

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

natives and immigrants, some deterioration of the settlement patterns from historical patterns, or both.

Recall that our skill ratio will be interacted with a period-indicator for early or late. Thus, we will not only have one first stage but two first stages for each of these interactions. However, Wooldridge (1997) suggests that it is more efficient not to interact the instrument with such an indicator variable, but instead use the first stage we presented in Appendix Table B.1, obtain the predicted values, $\hat{X}$, and interact them with our period dummies. We do this and obtain a very strong first stage for each sub-period of analysis as can be seen in Table 2, with skill mix tending to load onto the instrument from the appropriate period.[37]

5.2 Responses of capital

Having shown that our instrument is capable of generating significant variation in the endogenous variable, we now turn to explore how capital intensity responded to the change in the skill ratio generated by immigration. Table 3 shows results at the aggregate level, that is using only variation across areas. Columns (1) and (3) examine capital per worker and columns (2) and (4), capital per dollar of output. The first two columns present the OLS while the last two show the IV estimates. OLS seems to show limited responses of capital ratios to change in skill ratios: there is a positive and significant correlation between capital intensity and skill ratio in the early period. The IV estimates, on the other hand, suggest that capital per worker positively responded to an immigration-induced increase in skill ratios in both the early and the late periods, although the early effect is only significant in Panel A. The impact on capital-output ratios, on the other hand, is negative and significant for the early period when using 1890 as the last year of the early period and positive and significant for the late period with both cut-offs. From these aggregate results, we would thus conclude that capital-skill complementarity strengthened over the period and that capital and low-skill workers were q-complements in the early part of our sample.

A concern with the results in Table 3 is that they are potentially driven by shifts in the industry mix: that is, more less skilled workers may attract less capital intensive industries (e.g., Goldin and Katz, 1998; James and Skinner, 1985) and this would alter capital ratios. To address this, we ask, in the appendix, if the industry mix responded to a change in skill ratios. The results are presented in Table B.2. We find that in general, there is limited evidence that industry mix changed significantly in response to a change in the skill ratio. More importantly, combining these with the differences in factor intensity of each industry, we find very limited evidence

[37] Since the instrument is now the predicted values from the joint estimation across the entire 1860-1930 period, estimated in Appendix Table B.1, the first stage coefficients in Table 2 represent the size of the first stage relationship in a subperiod *relative to* the entire 1860-1930 period. So coefficients larger than one in the early period imply only that predicted immigration has a stronger relationship with actual changes in skill ratios in the early period than in the later period, *not* that predicted immigration has a larger than one-for-one association with skill ratios. Nevertheless, the coefficients are generally not statistically different than one.

overall that these shifts allowed the economy to absorb the area-level shift in skills availability or that they could explain the change we observed in terms of the capital relationship to skill. The exact calculations are presented in the Appendix. This suggests that the fact that we observed a changing elasticity between capital and skill in aggregate would not be due to changes across industries but more likely within-industry changes.

Given 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. Table 4 shows instrumental variables (IV) estimates of the relationship between skill mix and capital measures at the industry x area level.[38] The first 3 columns of each table focus on the capital per worker while the last 3 columns present the results for the capital-output ratios. The panels are organized as previously depending on the moment in which our sample is split between early and late periods. For each outcome and period, we successively increase the number of additional fixed effects, starting from none, to fixed effects for industries and finally, for industry-year fixed effects.[39]

Table 4 suggests that the results we obtained in Table 3 were not driven by shifts between industries since we observe a similar pattern in terms of changes in magnitudes and signs across periods but our statistical power is clearly reduced. We observe a negative impact of skill ratio on capital per worker and capital per output in the early period for both cut-offs. The results lose their significance once larger sets of fixed effects are introduced, though the sign remains the same. In the later period, we find that the skill-ratio increased significantly the capital per worker, a result that is not robust to the inclusion of multiple fixed effects. The F-statistics of the reduced form are similar to those of the IV, suggesting that our results are not driven by weak instruments. (The coefficients are statistically different from one period to the next whenever there is one coefficient statistically significantly different from 0). From the model, this suggests that capital-skill complementarity used to be much weaker in the early period than in the late period. Using our framework, this would imply that in the early period, capital was relatively more complementary with low- than with high-skill workers, but its relative complementarity with low-skilled workers fell (and its relative complementarity with skilled labor increased) as time passed. As we will discover below, the magnitudes of the positive coefficient in the late period may even suggest that capital and low-skill workers became q-substitutes.

Thus, while the statistical significance of some late period results is weaker than one would hope, the magnitudes are clearly suggestive of a change in the relationship of capital with skilled and unskilled labor as time went by. This is consistent with what some historians have previously argued, that in the nineteenth century, capital was a relative substitute of skilled labor,

[38]We do not present the OLS results but they show a positive association between both measures of capital intensity and the skill ratio with similar magnitude in the late and the early periods.

[39]It is also theoretically possible to control for industry x area effects, but by definition these are uncorrelated with the right-hand side variable which does not vary at this level. So doing so would have no effect on the slope estimates.

and became a relative complement of skilled labor only some time later in the nineteenth or early twentieth century. The argument is that early factories were low-skill and capital-intensive relative to the alternative, artisanal production. In light of this, it is interesting that we find no statistically significant association between skill supplies and establishment size in the early period (See results in Table B.3).[40] While not entirely ruling out that capital's response is due to a shift between "modes" of production, this is not consistent with the idea that this result is driven by the shift between artisanal and factory production. Another way to see it is as providing reassurance that results are really being driven by changes in production technique (and not confounded by establishment size, a concern raised in Katz and Margo, 2013).

OLS estimates both at the aggregate level and at the industry level would have not been able to tell us this. A standard story would be that OLS estimates are attenuated by measurement error. This seems a plausible contributor to bias in this context, with a crude self-reported measure of skill conditional on a large number of fixed effects. However, there may also be other sources of bias. 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 be drawn to the area but not to manufacturing, which could reduce the adoption of capital- and low-skill-intensive production techniques.

One may be worried that our measure of the value of capital may not be as close as to what we wish to measure since it includes land and buildings. We thus turn to our two alternative measures of capital, namely horsepower (which in some years is predicted from value of machinery and equipment) and fuel expenditures and rent of power. These two measures are only available from 1890 on, but we (very crudely) extrapolated their value for 1860 as well. However, since our instrument requires at least 2 years within each sub-period, this implies that we cannot get an estimate of the causal effect of a change in the skill ratio when the early period only includes 1860-1880. Thus, Table 5 includes only one panel instead of two for that reason. The format of the table mirrors that of the previous one except that for each outcome, we now have two different measures. Columns (1)-(3) and (7)-(9) measure capital from fuel expenditure and the others from horsepower and its proxy. A difference to keep in mind between this table and the previous one is that we have limited information for the early period –it is essentially an 1890 cross section– thus limiting our capacity to make comparisons. This may explain why in this table, we do not estimate a significant negative coefficient as we found previously for the early period. For both measures, we find strong, and positive effects of the skill ratio on capital per worker in the late period, suggesting that the exogenous arrival of more skilled workers increased the use of these measures of capital. The results for capital-output ratios are also positive and significant. The results for fuel expenditures remain significant after controlling for the full set of fixed effects. If

[40] This contrasts with Kim (2007), who finds an association between immigration, not parameterized by skill, and plant size.

we use our theoretical framework, we would again draw a similar analysis than before: fuel expenditures and horsepower became more complementary to high-skill workers around the turn of the twentieth century.

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

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

where

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

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

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

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

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

- If $\kappa < 0$, then capital and skills are q-substitutes and capital and low-skill workers are q-complements
- If $\frac{s_H}{s_L+s_H} > \kappa > 0$, then both types of labor are q-complements with capital, but capital is more complementary to low-skill labor than high-skill labor
- If $1 > \kappa > \frac{s_H}{s_L+s_H}$, then both types of labor are q-complements with capital, but capital is more complementary to high-skill labor than low-skill labor

- If $\kappa > 1$, then capital and high-skill labor are q-complements and capital and low-skill labor are q-substitutes

Recall in Section 4 we calculated that $s_L = 0.0787$ and $s_H = 0.5085$, which produces a cutoff of about $\frac{s_H}{s_L+s_H} = 0.866$. We perform this estimation and report the results in Table 6 where we also report a different estimate of κ for early and late periods using two different cut-offs in each panel, as before. The first three columns use our regressions of the value of capital, the next three use our fuel expenditures and the last three, our horsepower measure. For each of these outcomes, we also explore the impact of controlling for fixed effects.

We can see that we do gain some statistical power by imposing some structure on our estimates. We can now argue that capital increased the marginal productivity of low-skill labor in the early period when using the value of capital or fuel expenditures as our measure of K. Our measure of κ is statistically larger than 0 in all cases for capital and horsepower and it is also less than 1 except in one case. It is also smaller than 0.866 for capital and horsepower, although not statistically so. This would suggest that for the early period, capital was q-complements of both types of labor but capital was slightly more complementary to low-skill than to high-skill labor. For 1890-1930, we find a κ which is larger than one, implying that capital would have not altered the marginal productivity of low-skill workers or if anything, may have lowered it. When we divide our late period to include only 1900-1930, we find even larger values for κ, suggesting that capital became a q-substitute to low-skill labor around 1900. The difference between the early and late estimates for capital is statistically significant when using no industry controls in the top panel and when using industry fixed effects in the second. For fuel expenditures, the estimates are always different one from another. For horsepower, the difference is much less marked and never statistically significant. This may be because horsepower measures a type of capital that is exactly at the core of the Second Industrial Revolution and thus would not experience this break over time as other types of capital we presented; indeed horsepower per unit output increased tremendously over this period (e.g., Table 1.)

Overall, these "structural" results suggest that capital and high-skill labor (as measured by literacy) have been consistently q-complementary in manufacturing since at least 1860 but that this relationship was strengthened substantially around 1890-1900 when, in some of our estimates, it became so complementary that low-skill workers became substitutes for capital. This also seems to vary by type of capital, where technologies using horsepower appear to have been more complementary with high-skill workers than other types of capital. Furthermore, we have explored how sensitive our results are to our assumptions and have found little reason to believe that the results we present would look different if we had used the estimates of parameters for any other years.[41] In particular, given that s_H and ϕ_H were actually larger in the later period, the results we present are potentially an understatement in terms of the change we measure in κ.

[41] Results not presented but available upon request

Two main criticisms could be made about our results. The first is that immigration in itself was changing over this period and maybe the changing relationship we are capturing is simply due to the fact that capital was more complementary to the first wave of European migrants to America than the second. However, we do not find any evidence that counties that had a high share of the "Old" immigrants versus the "New" ones saw less of a change in κ. If anything, they may have observed a larger one, making that hypothesis less credible.[42] Secondly, one may think that if there was polarization in the economy over this period, our changing relationship could simply be due to the fact that within literate and illiterate groups, the type of workers was changing and that each type had a different level of complementarity with capital. While we cannot exclude entirely that possibility, we tried dividing each literacy group into the three types of occupations used in Katz and Margo (2013)'s classification (white collar, artisan, and low-skill workers) and assumed extreme differences in capital complementarity with each. We find no evidence that the shifting composition of literate and illiterate workers between these three groups of occupations by itself would have changed the estimated κ between periods in a way that is consistent with what we estimated.[43]

6 Parametric Specifications, Calibration and Simulation

Having estimated that the relationship between capital and skill has strongly changed over our period of study and being limited by data to study directly the wage effects of immigration, we now take a more parametric specification to explore how this changing relationship may have affected how the US economy was able to absorb changes in skill mix generated by migration.

6.1 Setup

In order to simulate the wage and capital accumulation impacts of immigration, we turn to a parametric form for our single-good model of production in Section 2. Capital-skill complementarity is generally modeled using a nested CES structure, which can either group together

[42] See Table B.4 for results.

[43] To lay out the issue explicitly, suppose there were really the three skill groups described in Katz and Margo (2013) – H^{km}, M^{km}, L^{km} (white collar, artisans, laborers). Each has a fixed relationship with capital, but the share of literate and illiterate workers in each evolves over time. In Katz and Margo (2013), middle-skill occupations, M^{km}, are the most substitutable for capital compared to H^{km} and L^{km}. So the worst case scenario for us would be that a declining concentration of literate workers in M^{km} would make it spuriously appear that the average complementarity of capital with literate labor was rising above the complementarity with illiterate labor. What we found through simulation, however, was that even extreme values of capital q-complementarity with H^{km} relative to M^{km} would not be able to generate a reversal over time in the average q-complementarity of capital with literate workers relative to illiterate workers. One way to explain this is that while it is true that literate workers decreased their concentration in M^{km} over time, illiterate workers *also* decreased their concentration in M^{km} over the same period. Specifically, the share of literate workers in middle-skill occupations fell from 56% to 23% 1860-1930, but the share of illiterate workers in middle-skill occupations also fell from 27% to 10% over the same period.

capital and skilled labor (e.g., Goldin and Katz, 1998; Krusell et al., 2000), or capital and unskilled labor (e.g., Autor et al., 2003; Lewis, 2011) in the inner nest. For example, the general form of the production function used in Goldin and Katz (1998) is

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

where $\rho > \theta$ implies capital is more complementary with high- than low-skill labor ($\rho < \theta$ implies the opposite). 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 in the position of H and L. In (12), $\theta > \rho$ instead implies relative capital-skill complementarity. Since there is not consensus on the "right" way to nest the production function, we will try it both ways, and see which fits the data better. Under (11):

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

while under (12)

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

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

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

under (11) and

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

under (12).

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

6.2 Parameter Values

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

To see this, Table 7 maps out the parameter estimates and relative wage 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).[44] The top panel assumes, as Goldin and Katz (1998) did, that the outer nest is Cobb-Douglas ($\rho = 0$). As a benchmark, we will start by assuming that capital is not more or less complementary to skill, i.e. is "skill neutral," by setting $\theta = \rho = 0$, shown in row 1. This implies that relative wages fall one-for-one as skill ratios rise. (More generally, the relative wage impact of a one unit increase in $ln(H/L)$ is given by $\rho - 1$ in the skill neutral case $\theta = \rho$ – see (15) and (16)).

Next, let us turn to choosing parameters consistent with our estimate of κ for 1860-80 of 0.7, shown in row 2 of the table. This implies a negative value of $\theta = -0.85$ when capital is nested with unskilled labor and a positive value of $\theta = 0.58$ when capital is nested with skilled labor. In both cases, this implies that capital is q-complementary with both skilled and unskilled labor, but more so with unskilled than skilled labor. In the capital-unskilled nesting, wage impacts are *larger* in magnitude than the capital neutral benchmark in row (1), as capital adjustments magnify the relative productivity impact of changes in skill supply. This does not happen here when capital is nested with skilled labor.

In contrast, as noted in section 2, if the response of capital output ratios to skill mix is positive ($\kappa > \frac{s_H}{s_L + s_H} \approx 0.866$) – so that capital and skill are relative complements – then the relative wage impacts are smaller than the benchmark case. Our estimate of $\kappa = 1.1$ for 1890-1930 from Table 6 implies the impossible $\theta > 1$ when capital is nested with skilled labor, which casts some doubt on the appropriateness of this nesting. However, when we nest capital with unskilled labor, row 3 of Table 7 shows we obtain a large positive estimate of $\theta = 0.77$ that is in the admissible range below one. In that case, the impact of the change in skill ratio on the relative wage is strongly attenuated by the response of capital, with magnitudes of about one third that of the "skill-neutral" benchmark case shown in the table's first row. Interestingly in modern data

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

and using a similar approach, Lewis (2011) estimates a κ only slightly more positive (albeit for different skill categories, high school dropouts and completers) than the one we obtain for the late period, potentially consistent with Goldin and Katz (1998)'s argument that modern capital-skill complementarity is a continuation of a similar relationship between labor and non-labor inputs in this earlier era. Rows 4 and 5 show that larger estimates of κ would imply even smaller wage impacts (such as the extreme case of Autor et al., 2003).

How sensitive are these relationships to different parameter choices? The pattern of relative magnitudes are not sensitive to the choice of our least well justified parameter ρ, the one which governs the elasticity of substitution between skill types. For example, the bottom panel shows the same set of simulations, with instead ρ set at 0.33, which is roughly what you would need to get to the consensus value for the elasticity of substitution between college and non-college labor in the modern U.S. labor market (e.g., Hamermesh, 1993). The absolute wage impacts are smaller in this panel (by design of the larger elasticity), but the proportional difference across rows varies in nearly the same way as the upper panel (for example, the estimates in row 8 are about one-third of those in row 6). The estimated wage impact in the later period would also be even smaller if, realistically, the capital or skill share were even larger in the later period.[45]

Interestingly, the estimates in the lower panel of Table 7 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.

[45] Additional discussion, including an example of impacts under different share parameters appears in Appendix B.

[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 is quite consistent with the wage impacts in rows 6-8 of the lower panel of Table 7.

6.3 Simulating the Impact of Immigration

The one unit increase in $ln(H/L)$ used in the Table 7 simulations may not be typical of the impact of immigration. Therefore we turn to simulations based on the actual experience of the U.S. economy with immigration during the period of our estimates. Table 8 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 $\rho = 0.33$, $s_L = 0.08$, and $s_H = 0.51$. Since nesting capital and unskilled labor seems to fit the data better, we will focus on simulations using that nesting.

Panel A of Table 8 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 of 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 7, row 7, column 5, removing immigrants who came between 1860 and 1880 would have raised skilled relative wages by about 8 percent, which is equivalent to saying net immigration during that era raised unskilled relative wages by roughly 8 percent. Capital intensity was also rising during this era, and our complementarity estimates suggest this also would have raised unskilled relative wages. Thus both immigration and technological change during this era likely had the effect of compressing the wage distribution of natives.

The remaining rows of Table 8 examines what would have happened if the literacy test Congress passed in 1897 had become law.[48] 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). Panel C asks, therefore, what would the impact of the wave of southern and eastern European immigration have been if the production technology had not changed?

To implement this simulation, we drop from the Census of Population sample (Ruggles et al., 2010) any illiterate immigrants who arrived after 1897, and compute the counterfactual skill ratios. Column (2) of Table 8 shows that this raises skill ratios over time, by 1920 substantially, about 35 percent. To do the middle panel simulations, we take the wage elasticity in row 8 of Table 7. Column (4) shows that the literacy test might have lowered skilled relative wages by 7 percent; put differently, the illiterate arrivals who stayed in the U.S. after 1897 appear to have lowered unskilled relative wages by 7 percent. This is quite a modest wage impact given

[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 as actually observed.

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

the 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.[49] However, even these alternatives are quite modest compared to what the relative wage impact would have been 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 – the ability to heavily substitute away from it at a fixed rental rate – may have played an important role in the absorption of large waves of immigrants at the turn of the twentieth century.

We would like to test this more directly by estimating how much immigration-induced changes in the skill ratio affected relative wages in manufacturing. Measuring relative wages directly is challenging, however, as individual-level wage data are not available until 1940 in IPUMS. Wage data by "skill" – salaried officials and wage workers – only becomes available in the Census of Manufactures starting in 1890. Thus, at best we are only able to analyze the late period. We have used this data to construct a crude proxy for the relative wage of literate workers (by assuming, as above, that there is no return to literacy within production category). Using this proxy, we estimate that changes in skill ratios have a small, positive and not significant effect on wage ratios in all specifications.[50] This may be because the approximation of the wage ratio is just too crude and may be confounded by compositional changes in who makes up salaried officials and wage workers as literacy rates change. However, they are also consistent with the effect of the skill ratio on wages being muted by changes in capital-ratios.

7 Conclusions

Our analysis suggests that immigration between 1860 and 1930 was a sufficiently important shock to the local labor force to alter skill ratios in urban counties. It also suggests that manufacturing capital intensity responded to immigration-induced changes in skill ratios at the aggregate level differently across periods, a pattern due mostly to changes *within* industry instead of between.[51] The estimated responses support the notion that capital relatively substituted for skilled labor in nineteenth century manufacturing. This appears to have dramatically changed around the turn of the century, when low-skill workers became substitutes for capital and ushered in the level of capital-skill complementarity we see in modern times. This shift appears to coincide

[49] This also leaves out that the vast majority of native-born workers, who were literate, would have had higher, not lower, wages as a result of this inflow, according to our simulations.

[50] Results available upon request.

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

with the Second Industrial Revolution suggesting that something in that new way of production altered the relationship between capital and skill.

What caused the Second Industrial Revolution to alter the relationship between capital and skill? This is still left to be explored but historians argue that electricity, by altering the way the production could be segmented and divided, may have allowed machines to play a role in the new production lines that was before impossible. We leave this to future research.

We are also only able to use simulations based on fitting our estimates to a parametric production function to measure the potential wage impact that immigration had on US local economies at the time. These simulations suggest the importance of the early twentieth century production technology in allowing the U.S. economy to absorb the wave of southern and eastern European migrants with only a modest decline in less-skilled wages. This was possible because the production technology allowed a sufficient rate of substitution away from capital (at a fixed rental rate) in response to the less-skilled labor shock. Under the older production technology in which capital complemented low-skill labor, this would not have been possible. This historical context thus reveals that the way in which non-labor inputs adjust to labor mix shocks can play a critical role in the economy's ability to adapt to such shocks. Research in other contexts may be warranted.

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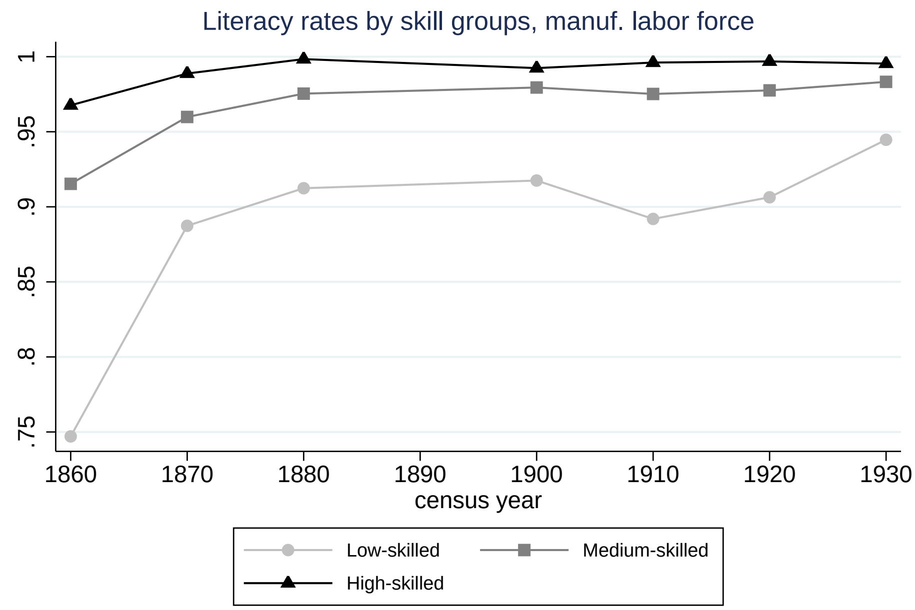
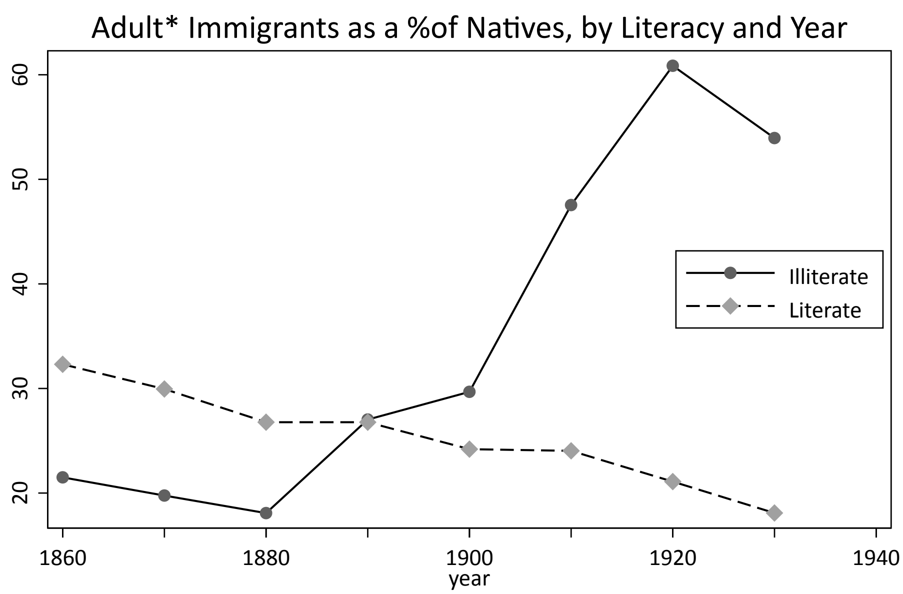
Figure 1. Literacy rates by occupational groups within manufacturing



Source: Own calculations from IPUMS census data. Skill group definition from Katz & Margo (2013).

Figure 2. Fraction of foreign-born US residents by literacy status



Data Sources: U.S. Censuses of Population (Ruggles et al., 2010), except 1890 from United States Census Office (1897).
*Population aged 15+. 1890 based on (foreign white + 'colored non-negro')/(native white + 'negro').

Figure 3. Instrument: Graphical Example

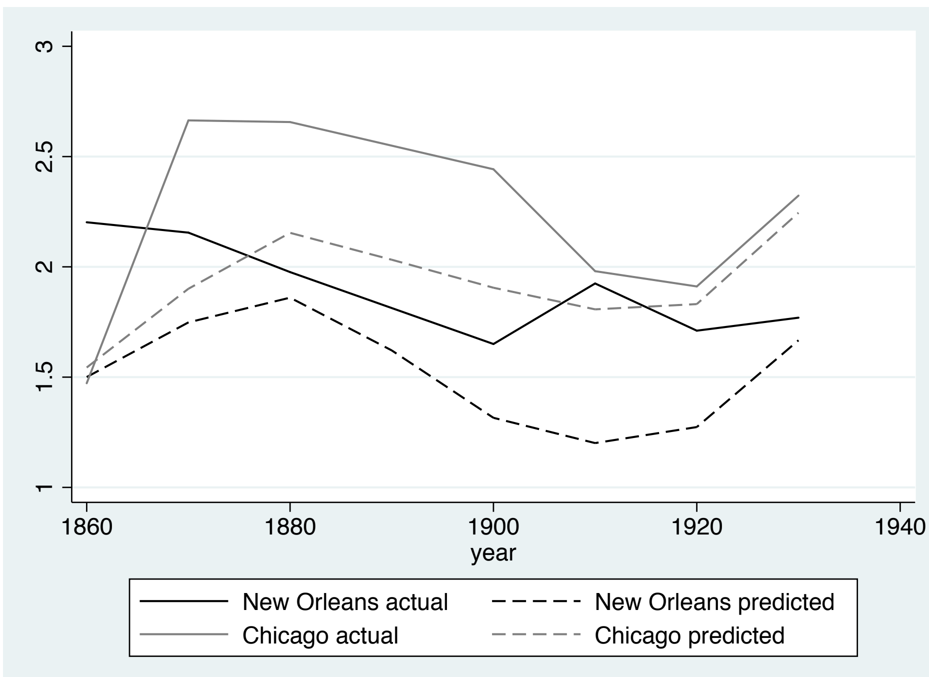


Table 1. Descriptive Statistics on Area x Industry Sample

Variable	Early period			Late period		
	# cells	Mean	Std. Dev.	# cells	Mean	Std. Dev.
Panel A: Early Period is 1860-80						
ln(K/N)	16668	6.650	0.984	20635	7.217	0.991
ln(K/Y)	16667	-0.105	0.827	20613	0.032	0.724
ln(Fuel/N)	6750	-5.277	1.678	19542	2.916	1.417
ln(Fuel/Y)	6750	-11.907	1.765	19558	-4.288	1.189
ln(Horsepower/N)	6750	-5.277	1.678	20497	-0.260	1.242
ln(Horsepower/Y)	6750	-11.907	1.765	20516	-7.441	1.119
ln(H/L)	16713	1.921	0.783	23541	2.980	0.687
$\ln(\widehat{H/L})$	16713	1.335	0.223	23541	2.204	0.442
Panel B: Early Period is 1860-90						
ln(K/N)	22454	6.673	0.960	14849	7.405	0.966
ln(K/Y)	22453	-0.100	0.796	14827	0.077	0.729
ln(Fuel/N)	11784	-2.158	3.953	14508	3.225	1.243
ln(Fuel/Y)	11784	-8.878	3.865	14524	-4.105	1.038
ln(Horsepower/N)	12528	-3.143	2.737	14719	-0.107	1.229
ln(Horsepower/Y)	12528	-9.860	2.662	14738	-7.430	1.143
ln(H/L)	22500	2.126	0.840	17754	3.065	0.660
$\ln(\widehat{H/L})$	22500	1.439	0.264	17754	2.357	0.403

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

Table 2. First stage regressions-by period

	Early			Late		
	(1)	(2)	(3)	(4)	(5)	(6)
			Panel A: Early Period is 1860-80			
$\hat{X}$*(1860to 1880)	3.431***	3.430***	3.512***	-0.000	-0.005	-0.000
	(1.295)	(1.284)	(1.296)	(0.000)	(0.003)	(0.000)
$\hat{X}$*(1890 to 1930)	-0.000	-0.002	-0.000	0.680**	0.682**	0.658**
	(0.000)	(0.003)	(0.000)	(0.278)	(0.278)	(0.281)
R^2	0.939	0.940	0.942	0.978	0.978	0.978
			Panel B: Early Period is 1860-90			
$\hat{X}$*(1860-1880)	1.273***	1.274***	1.282***	0.000	-0.000	-0.000
	(0.334)	(0.332)	(0.332)	(0.000)	(0.001)	(0.000)
$\hat{X}$*(1900-1930)	-0.000	-0.001	0.000	0.698***	0.698***	0.675***
	(0.000)	(0.004)	(0.000)	(0.231)	(0.230)	(0.230)
R^2	0.936	0.936	0.938	0.990	0.990	0.991
Fixed Effects:						
Year	Y	Y	Y	Y	Y	Y
Area	Y	Y	Y	Y	Y	Y
Industry	N	Y	Y	N	Y	Y
Ind. x Year	N	N	Y	N	N	Y

Outcome is ln(literate/not literate) in the age 15+ population from IPUMS, except 1890, which uses published tabulations of the age 10+ population of the area. $\hat{X}$ represents the predicted value of this ln skill ratio based on the average relationship between it and the instruments, which apportions immigrants to counties by country of birth (and natives by state of birth) based on their locations in an earlier base year (1850 or 1880) – see text and table B.1. Standard errors in parentheses, calculated to be robust to arbitrary error correlation with area. Sample is restricted to industry-years where at least 2 cities in that year reported a given industry. N=37,278. Significance levels: * 10%, ** 5%, ***1%.

Table 3. Estimation with Aggregate Data

	OLS		IV	
	K/N	K/Y	K/N	K/Y
	(1)	(2)	(3)	(4)
	Panel A: Early Period is 1860-80			
ln(H/L)*(1860 to 1880)	0.094**	0.021	0.389**	-0.135
	(0.045)	(0.050)	(0.184)	(0.184)
ln(H/L)*(1890 to 1930)	0.036	-0.150	1.151**	0.958**
	(0.062)	(0.203)	(0.454)	(0.426)
R^2	0.907	0.935	0.892	0.923
RootMSE	0.799	0.721	0.715	0.652
	Panel B: Early Period is 1860-90			
ln(H/L)*(1860 to 1890)	0.082**	0.014	0.060	-0.323*
	(0.039)	(0.043)	(0.195)	(0.165)
ln(H/L)*(1900 to 1930)	-0.080	-0.385	1.281**	0.905*
	(0.145)	(0.334)	(0.541)	(0.470)
R^2	0.908	0.937	0.898	0.928
RootMSE	0.802	0.718	0.693	0.633

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

Table 4. Manufacturing outcomes, **Instrumental Variable Estimates**

	Capital/Worker			Capital/Output		
	(1)	(2)	(3)	(4)	(5)	(6)
	Panel A: Early Period is 1860-80					
ln(H/L)*(1860 to 1880)	-0.040	-0.041	0.015	-0.210	-0.223	-0.185
	(0.130)	(0.129)	(0.135)	(0.196)	(0.204)	(0.198)
ln(H/L)*(1890 to 1930)	0.661**	0.259	0.214	0.445	0.179	0.159
	(0.320)	(0.225)	(0.227)	(0.292)	(0.248)	(0.262)
R^2	0.279	0.555	0.607	0.080	0.272	0.345
RootMSE	0.881	0.692	0.651	0.758	0.675	0.640
Red. Form F-Stat (early)	0.094	0.099	0.013	1.155	1.154	0.779
Red. Form F-Stat (late)	9.939	1.685	1.088	3.352	0.566	0.399
	Panel B: Early Period is 1860-90					
ln(H/L)*(1860 to 1880)	-0.208*	-0.087	-0.030	-0.343*	-0.242	-0.204
	(0.120)	(0.099)	(0.097)	(0.177)	(0.163)	(0.147)
ln(H/L)*(1890 to 1930)	0.635**	0.333	0.289	0.684*	0.493	0.451
	(0.321)	(0.262)	(0.256)	(0.352)	(0.309)	(0.313)
R^2	0.282	0.554	0.606	0.057	0.258	0.334
RootMSE	0.879	0.693	0.651	0.768	0.681	0.645
Red. Form F-Stat (early)	3.743	0.798	0.095	4.635	2.416	2.008
Red. Form F-Stat (late)	8.357	2.309	1.753	8.643	4.557	3.649
Fixed Effects:						
Industry	N	Y	Y	N	Y	Y
Ind. x Year	N	N	Y	N	N	Y

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

Table 5. Alternative capital measures, **Instrumental Variable Estimates**

	Capital/Worker						Capital/Output					
	Fuel exp.			Horsepower			Fuel expenditures			Horsepower		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	Panel A: Early Period is 1860-90											
ln(H/L)*(1860 to 1890)	-0.313	-0.050	-0.059	0.191	0.314	0.227	-0.570	-0.347	-0.405	-0.092	0.045	-0.088
	(0.384)	(0.314)	(0.342)	(0.472)	(0.471)	(0.470)	(0.492)	(0.419)	(0.423)	(0.539)	(0.513)	(0.505)
ln(H/L)*(1900 to 1930)	1.137***	0.575**	0.572**	1.079**	0.339	0.246	1.180***	0.729**	0.740**	1.112**	0.492	0.402
	(0.429)	(0.256)	(0.262)	(0.441)	(0.299)	(0.291)	(0.450)	(0.297)	(0.311)	(0.473)	(0.345)	(0.338)
R^2	0.868	0.910	0.925	0.679	0.794	0.846	0.849	0.885	0.902	0.622	0.726	0.791
RootMSE	1.242	1.025	0.935	1.266	1.014	0.876	1.218	1.065	0.980	1.232	1.050	0.917
Red. Form F-stat 1860 to 1890 Sample	0.639	0.024	0.028	0.181	0.573	0.264	1.409	0.668	0.862	0.028	0.008	0.028
Red. Form F-stat 1900 to 1930 Sample	19.628	8.748	7.829	8.617	1.259	0.718	24.188	16.411	14.698	8.474	2.208	1.618
Fixed Effects:												
Industry	N	Y	Y	N	Y	Y	N	Y	Y	N	Y	Y
Ind. x Year	N	N	Y	N	N	Y	N	N	Y	N	N	Y

All outcomes in logs. All regressions include fixed effects by area and by year and are weighted such that each area-year is given the same weight. Right-hand side variable is ln(literate/not literate) in the age 15+ population (except 1890, which uses published tabulations of the age 10+ population of the area). Standard errors in parentheses, calculated to be robust to arbitrary error correlation with area. Sample is restricted to industry-years where at least 2 cities in that year reported a given industry. N=26,292 for fuel expenditures and N=27,247 for horsepower. Significance levels: * 10%, ** 5%, ***1%. *Horsepower* includes imputed measures for 1880 and 1890 from machinery and equipment. See Data Appendix.

Table 6. Structural estimate of relative capital-skill complementarity

	Capital			Fuel expenditures			Horsepower		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
					Panel A: Early Period is 1860-80				
κ*(1860 to 1880)	0.740***	0.734***	0.792***						
	(0.166)	(0.170)	(0.172)						
κ*(1890 to 1930)	1.547***	1.132***	1.090***						
	(0.355)	(0.264)	(0.271)						
					Panel B: Early Period is 1860-90				
κ*(1860 to 1890)	0.557***	0.691***	0.750***	0.380	0.673*	0.640	0.963*	1.114**	0.992*
	(0.157)	(0.132)	(0.122)	(0.479)	(0.387)	(0.413)	(0.565)	(0.551)	(0.549)
κ*(1900 to 1930)	1.632***	1.325***	1.273***	2.219***	1.605***	1.608***	2.145***	1.326***	1.217***
	(0.386)	(0.321)	(0.317)	(0.509)	(0.310)	(0.319)	(0.530)	(0.367)	(0.355)
Fixed Effects:									
Industry	N	Y	Y	N	Y	Y	N	Y	Y
Ind. x Year	N	N	Y	N	N	Y	N	N	Y

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

Table 7. 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 κ (1)	s_H (2)	s_L (3)	K Nested w/Unskilled Implied θ (4)	%Impact on skilled wg premium[a] (5)	K Nested w/Skilled Implied θ (6)	%Impact on skilled wg premium[a] (7)
Panel A: Assuming $\rho = 0$							
(1) Benchmark, $\rho = \theta$	$s_H/(s_H + s_L)$	$\in (0,1)$	$\in (0,1)$	0.00	**-1.00**	0.00	**-1.00**
(2) This Paper, 1860-1880	0.70	0.51	0.08	-0.85	**-1.50**	0.58	**-0.92**
(3) This Paper, 1890-1930	1.10	0.51	0.08	0.77	**-0.29**	N/A[d]	
(4) Lewis (2011a)[c] 1980-2000	1.15	0.51	0.08	0.90	**-0.14**	N/A[d]	
(5) Autor, Levy, Murnane (2003)	N/A	$\in (0,1)$	$\in (0,1)$	1.00	**0.00**	1.00	**0.00**
Panel A: Assuming $\rho = 0.33$							
(6) Benchmark, $\rho = \theta$	$s_H/(s_H + s_L)$	$\in (0,1)$	$\in (0,1)$	0.33	**-0.67**	0.33	**-0.67**
(7) This Paper, 1860-80	0.70	0.51	0.08	-0.24	**-1.00**	0.72	**-0.62**
(8) This Paper, 1890-30	1.10	0.51	0.08	0.85	**-0.19**	N/A[d]	
(9) Lewis (2011a)[c] 1980-2000	1.15	0.51	0.08	0.93	**-0.09**	N/A[d]	
(10) Variant of (5)	N/A	$\in (0,1)$	$\in (0,1)$	1.00	**0.00**	1.00	**0.00**

Notes: [a]Simulated impact of a one unit increase in $\ln(H/L)$, where H represents skilled (literate) and L unskilled (illiterate) labor, on the returns to literacy (skilled-unskilled log wage gap) in a competitive single-good economy represented by the production function (12) in column (5) and (11) in column (7), where K represents capital. This impact is approximated as (16) in column (5) and (15) in column (7) where s_L represents low-skill and s_H skilled labor's share of output, and κ represents the relative cross partial of low-skill labor, estimated in Table 6.

[b] Estimates of κ from Table 6 are converted to an estimate of θ (for the given value of ρ, s_H and s_L) using (14) when capital is nested with unskilled labor and (13) when capital is nested with skilled labor.

[c] Lewis estimates $d\ln(K/Y)/d(L/H) = -0.56$, (with L, H high school dropouts and completers, respectively) which evaluated at the mean L/H of 0.3 (in Lewis's sample) converts to an elasticity of about $\varepsilon = 0.17$, which is converted to an estimate of κ using that $\kappa = (\varepsilon + s_H)/(s_L + s_H)$

[d]$\kappa > 1$ is not feasible under this parameterization, as it would require $\theta > 1$.

Table 8. Impact of Counterfactual Immigration Flows on Skilled Relative Wage

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

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

Online Appendix – Not for Publication

A Derivation of Parametric Model

A.1 Derivation of Model Version 1

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

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

and that

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

Combining these equations we obtain that κ is given by

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

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

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

and

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

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

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

Substituting in for $d\ln(K/H)$ for $(\kappa-1)d\ln(H/L)$ produces

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

A.2 Derivation of Model Version 2

In this case:

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

and that

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

Combining these, we obtain that κ is given by

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

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

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

so relative wages are

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

Taking the log differential of this expression we obtain

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

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

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

B Additional Results

B.1 Restricted First Stage

In Table B.1 we present the first stage regressions which restrict the coefficients to be the same in the early and late period. As is referenced in Section 5, the predicted values from this are what are actually used in the construction of the instrument interacted with period, following Wooldridge (1997).

Table B.1. First stage regressions

	(1)	(2)	(3)
Panel A: Early Period is 1860-80			
$\ln(\widehat{H/L})$	0.719***	0.718***	0.697***
	(0.203)	(0.202)	(0.199)
R^2	0.875	0.876	0.880
Panel B: Early Period is 1860-90			
$\ln(\widehat{H/L})$	0.950***	0.951***	0.947***
	(0.188)	(0.187)	(0.187)
R^2	0.875	0.876	0.880
Fixed Effects:			
Year	Y	Y	Y
Area	Y	Y	Y
Industry	N	Y	Y
Ind. x Year	N	N	Y

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

B.2 Alternative adjustment mechanisms

Our estimates were, in some cases, sensitive to industry mix controls. So we now directly explore whether the change in skill availability within an area altered the industry mix. The difference between our aggregate results and our industry-level results may indicate that there is some change by industry mix but it is difficult to quantify. We present, in Table B.2, 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 into categories, as running the share of each industry separately would be too lengthy and difficult to interpret. As a first approximation, we separated industries based on their capital/labor and literate/non-literate workers ratios at the national level in the first year that variable was provided in the data (namely 1860 for K/N and 1890 for H/L).[52] We find no strong evidence indicating that the aggregate skills ratio influenced significantly industry composition and the allocation of low-skill workers to different industries. We find only one significant coefficient which suggests that industries in the second quartile of the H/L distribution expanded more in the 1860-1890 period in response to an increase in the local H/L ratio, at the expense of all other quartiles.

Combining these with the difference in factor intensity of each industry, we find very limited evidence overall that these shifts allowed the economy to absorb the area-level shift in skills availability. What we do here is we multiply the response in terms of size of industry by the factor-ratio in each of these quantiles and sum them up. By dividing that sum by the average factor ratio in the economy, we then obtain what is the change in percent that would have been generated through shifts of industries alone. We find that in all periods, except 1860-1880, taking the coefficients at face value, the change in industry composition would have actually lowered the capital per worker in each county. The estimates range from a 3 percent decrease in 1900-1930 to 16 percent decrease in 1890-1930. In 1860-1880, the results would suggest an increase of 22 percent. Given that, if anything, the results we obtain here go in the opposite direction as our estimated impacts at the disaggregated results, this suggests a limited role for industry-shift responses. These are simply averages and given the fact that none of the coefficients are significant, they should not be perceived as in any way precise. Nevertheless, they suggest shifts across industries are unlikely to drive the pattern we observe in aggregate.

The results for the skill ratio are all extremely small, suggesting that the manufacturing sector did not absorb the change in skill ratios by altering its industry mix. Furthermore, we do not see much evidence of a change as time goes by suggesting that we cannot justify the pattern we identify as time passes.

Overall, these results seem to suggest a small 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 and the coefficient for the earlier period is positive and not significant.[53]

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

[53] Results available upon request.

Table B.2. Impact on industry composition (share of low-skill workers employed)

	Ranked by their K/L			Ranked by their H/L		
Quartile:	1	2	3	1	2	3
			Panel A: Early Period is 1860-80			
ln(H/L)*Early	-0.063	-0.086	0.026	0.019	0.106**	-0.121**
	(0.059)	(0.063)	(0.080)	(0.049)	(0.051)	(0.053)
ln(H/L)*Late	0.131	-0.058	0.003	-0.073	0.155	0.094
	(0.149)	(0.142)	(0.157)	(0.182)	(0.146)	(0.114)
Red. Form F-stat (early)	0.501	3.128	0.058	0.098	2.335	9.937
Red. Form F-stat (late)	0.632	0.167	0.001	0.103	0.873	0.567
			Panel B: Early Period is 1860-90			
ln(H/L)*Early	-0.007	-0.016	0.066	0.000	0.169***	-0.054
	(0.075)	(0.046)	(0.081)	(0.061)	(0.063)	(0.046)
ln(H/L)*Late	0.078	-0.029	-0.057	-0.040	0.094	0.041
	(0.133)	(0.147)	(0.143)	(0.164)	(0.119)	(0.095)
Red. Form F-stat (early)	0.002	0.035	0.260	0.026	4.891	0.826
Red. Form F-stat (late)	0.241	0.026	0.101	0.393	0.425	0.122
Average K/L or H/L	335.006	620.050	955.658	5.627	5.749	5.917

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

We also test whether there is a relation to firm size, which can be considered a proxy of factory and modern production rather than artisan installations. Our instrumental variable estimates suggest that the effect of the skill ratio is more positive in the second half, but only 2 of our estimates is statistically different from 0, as can be seen from Table B.3.

Table B.3. Firm size (ln employment) and skill ratios

	Ordinary Least Squares			Instrumental Variables		
	(1)	(2)	(3)	(4)	(5)	(6)
			Panel A: Early Period is 1860-80			
ln(H/L)*Early	0.136***	0.139***	0.134***	0.059	0.112	0.080
	(0.045)	(0.036)	(0.036)	(0.244)	(0.204)	(0.196)
ln(H/L)*Late	0.037	0.047	0.064**	0.501*	0.318	0.485*
	(0.034)	(0.030)	(0.027)	(0.291)	(0.232)	(0.277)
R^2	0.157	0.369	0.470	0.150	0.366	0.465
RootMSE	1.232	1.068	0.987	1.232	1.064	0.978
			Panel B: Early Period is 1860-90			
ln(H/L)*Early	0.136***	0.139***	0.129***	-0.282	-0.120	-0.174
	(0.040)	(0.032)	(0.031)	(0.244)	(0.192)	(0.171)
ln(H/L)*Late	-0.008	0.019	0.031	0.438	0.420	0.430
	(0.048)	(0.044)	(0.042)	(0.298)	(0.282)	(0.302)
R^2	0.155	0.367	0.469	0.142	0.361	0.462
RootMSE	1.234	1.069	0.988	1.238	1.068	0.980
Fixed Effects:						
Industry	N	Y	Y	N	Y	Y
Ind. x Year	N	N	Y	N	N	Y

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

B.3 Separating Old and New Immigrant Groups

The following table estimates the structural parameter κ by period, but including an interaction with a dummy indicating whether a county had a share of immigrants that was above 0.765% in 1880 (national share of new immigrants from Census) that were from the countries that Goldin (1994) identifies as being "new immigrant sources." Specifically, these countries are Bulgaria, Croatia, Czechoslovakia, Greece, Hungary, Italy, Montenegro, Poland, Portugal, Romania, Russia, Serbia, Spain, Turkey, Yugoslavia, Baltic Republics and non-German speaking immigrants from Austria.

In that table, we find limited evidence that the change in the parameter κ we document is driven by a change in the composition of immigrants. While some estimates are statistically significantly different from 0, most of them are in the opposite direction that would be needed to explain the evolution of κ. For example, in many instances, we find that counties that had more newer immigrants had a smaller estimate of κ than those with more immigrants from older source countries. Since the source countries became more and more "new" over the period we study, this would suggest that our estimate of κ would have increased less in counties where the shift in the composition of immigrants was more pronounced. The same is found when we see, in the bottom panel, that the estimate of κ would have been higher in counties with a higher initial fraction of new immigrants in the early period than in others. This suggests that, without the change in composition of immigrants, we may have observed an even larger change in κ.

Table B.4. Structural estimate of relative capital-skill complementarity

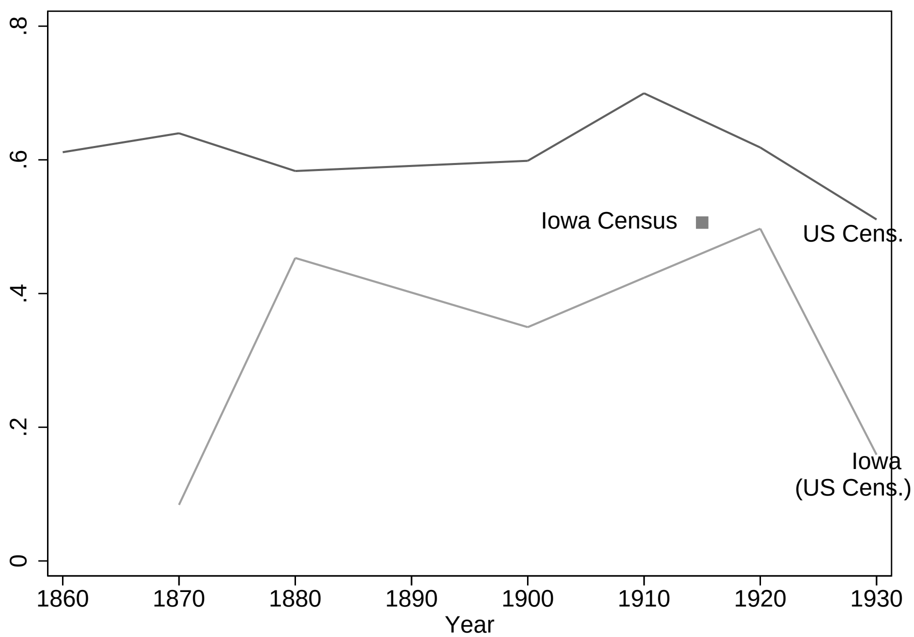
	Capital			Fuel expenditures			Horsepower		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
					Cut-off in 1880				
κ*Early	0.725***	0.720***	0.778***						
	(0.165)	(0.171)	(0.177)						
κ*Late	1.321***	1.003***	1.039***						
	(0.190)	(0.162)	(0.178)						
κ*Early*NewImm	0.115	0.106	0.108						
	(0.085)	(0.087)	(0.076)						
κ*Late*NewImm	-0.200**	-0.115	-0.041						
	(0.098)	(0.093)	(0.079)						
					Cut-off in 1890				
κ*Early	0.545***	0.680***	0.737***	0.255	0.497	0.485	0.830*	0.950**	0.825*
	(0.149)	(0.127)	(0.121)	(0.465)	(0.383)	(0.399)	(0.492)	(0.452)	(0.468)
κ*Late	1.518***	1.269***	1.298***	1.993***	1.534***	1.525***	1.895***	1.267***	1.212***
	(0.285)	(0.248)	(0.273)	(0.377)	(0.259)	(0.252)	(0.439)	(0.350)	(0.325)
κ*Early*NewImm	0.154**	0.127**	0.121***	-0.114	-0.162	-0.152	-0.137	-0.173	-0.186
	(0.068)	(0.059)	(0.047)	(0.126)	(0.111)	(0.123)	(0.129)	(0.119)	(0.127)
κ*Late*NewImm	-0.154	-0.077	0.032	-0.305**	-0.098	-0.107	-0.334***	-0.080	-0.006
	(0.118)	(0.111)	(0.101)	(0.140)	(0.103)	(0.113)	(0.130)	(0.086)	(0.079)
Fixed Effects:									
Industry	N	Y	Y	N	Y	Y	N	Y	Y
Ind. x Year	N	N	Y	N	N	Y	N	N	Y

All regressions include fixed effects by area and by year and are weighted such that each area-year is given the same weight. A corresponds to the ratio of the cross-partial derivative of the production function with respect to capital and illiterate labor over the sum of the cross-partial derivatives with respect to capital and each type of labor. Standard errors in parentheses, calculated to be robust to arbitrary error correlation with area. Sample is restricted to industry-years where at least 2 cities in that year reported a given industry. N=37,312. Significance levels: * 10%, ** 5%, ***1%. K includes capital imputed for 1930 from horsepower and *Horsepower* includes imputed values for 1880-1890 from machinery and equipment. See Data Appendix.

B.4 Robustness checks for simulations

In the simulations in section 6, the estimates of s_H and s_L used were calculated from aggregate data assuming that within occupational groups, there are no "returns" to literacy, that is, within each group, namely production and non-production workers, each worker received the same wage. In fact, to the best of our ability to measure it, the "return" to literacy, that is $ln(w_H/w_L)$ may have been around 50% over most of the years of our sample. We estimated this using the Iowa Census (Goldin and Katz, 2010), which has actual data on earnings, and in the U.S. Censuses of Population (Ruggles et al., 2010), using the 1950 "occupation score" (that is, the mean wages in the person's reported occupation in the 1950 census). We limited it to the sample of urban native-born who are at least age 20. Figure B.1 shows our estimates of the return to literacy by year.[54]

Figure B.1. Estimates of returns to literacy, by Census year



We are using that $\phi_H = 0.85$ and $ln(w_H/w_L) = 0.5$, which means that $H/L = 5.7$ and that the relative wage bills $\frac{H}{L}\frac{w_H}{w_L} = e^{0.5} * 5.7 = 9.34$. Given this, we could think that the estimates of s_H and s_L that would be potentially more realistic would be $s_H = 0.53$ and $s_L = 0.06$, which is not that different than what we are using. The results for our estimates of κ are robust to these changes; if anything, sensitivity of wage responses to the level of κ was shown in Table 7 with these alternative share parameters.

[54] 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.

C Data Appendix

This section covers some more of the details of the data sources and construction for the manufacturing data, and for the right-hand side variables (literacy ratio and the instrument).

C.1 Data Sources by Decade

The exact location of the tables used to construct our manufacturing outcomes are shown below.

C.1.1 1870 and covers 1850-1870

Table VIII(B), pp. 394-408 in Volume III, 1870 Census.

C.1.2 1900 and covers 1880-1900

Table 1, pp. 3-17 in Volume VII, 1900 Census.

C.1.3 1910

Table I, pp. 507-517 in Volume VIII, 1910 Census.

C.1.4 1920

Table 52, pp. 278-295 in Volume VIII, 1920 Census.

C.1.5 1930

Table 1, pp. 310-322 in Volume I, 1930 Census.

C.2 Imputed Capital Stock

Table C.5 shows the availability of variables in the manufacturing census tabulations by year. Not all variables are tabulated in all available years (even if they were in the underlying surveys). For example, data on capital stocks has always been collected, but was never tabulated after 1920. Employment and value added are always available.

Table C.5. Manufacturing Variables by Year

Variables	Years
Capital	1860-1920
Value of Machinery	1890-1900
Horsepower	1910-1930
Fuel expenditures	1890-1930
Number of Workers	1860-1930
Value added	1860-1930

To extend our main outcome to 1930, we used the 1910-1920 samples to run a regression of ln(Capital) on ln(Horsepower), controlling for year, area, and industry effects. From these estimates we imputed that $ln(\widehat{capital}) = 0.77839346 * ln(Horsepower)$. The relationship between horsepower and capital is very strong; the predicted values from 1910 and 1920 from this regression are quite close to the actual values.

Recall that we also examine the horsepower variable directly. It represents the horsepower of rated machinery, which is likely closer to the capital variable of interest in terms of replacing manual labor. Unfortunately, the tabulated series on this is quite short, running just 1910-1930. To extend the series backwards, we would like to use the closest variable to it, the value of machinery, which was tabulated in 1890 and 1900. Unfortunately, there is no overlap in the city-level tabulations of these variables from which to do the imputations. To address this, we turn to a 1900 *state* level (aggregate) tabulation which included both the value of machinery and horsepower. The relationship between these two at this level is $\widehat{horsepower} = 0.004 * Machinery$, which was applied to the 1890 and 1900 data to extend the horsepower variable back to 1890.

We also examine fuel expenditures as a third outcome. In each case, the regression outcome variable is the natural log of the capital variable divided by either the number of workers or value added. Horsepower and fuel expenditures only begin in 1890. To get some kind of estimates for the early period using these variables, we essentially put in blank cells for 1860 (and just for 1860: there remains no data for 1870 or 1880 in the regressions which use these variables). Specifically, we enter 0.1 for the value of horsepower and fuel expenditures in all 1860 cells. This is motivated by the microdata available for 1860 suggest that fuel expenditures and machinery horsepower in this era was trivial – see Atack and Bateman (1999) for a description of this microdata.

C.3 Industry Matches

Industries were matched across census tabulations using tabulated crosswalks in years after 1900, and by hand before that. Table C.6 gives our final set of industry crosswalks.

Table C.6. Detailed Industry Matching

Industry "Aggregate" and Census Industries Included		
	Industry 1	
Biscuit, crackers, and pretzels	Confectionery and ice cream	Meat packed pork
Blended and prepared flour made from purchased flour	Cooking and other edible fats and oils, not elsewhere classified	Meat packing, wholesale
Bread and crackers	Cured fish	Mustard
Bread and other bakery products	Feeds, prepared, for animals and fowls	Mustard, ground
Bread and other bakery products (except biscuit, crackers, and pretzels)	Fish and oysters, canned	Oysters, canning and preserving
Bread, crackers, and other bakery products	Fish cured and packed	Pickled fruits and vegetables and vegetable sauces and seasonings
Candy and other confectionery products	Fish, canning and preserving	Pickles, preserves, and sauces
Canned and dried fruits and vegetables (including canned soups)	Food preparations	Prepared feeds (including mineral) for animals and fowls
Canned fish, crustacea, and mollusks	Food preparations animal	Preserves and sauces
Canning and preserving	Food preparations vegetable	Preserves, jams, jellies, and fruit butters
Canning and preserving, fish	Food preparations vermicelli & macaroni	Provisions
Canning and preserving, fruits and vegetables	Food preparations, not elsewhere classified	Salad dressings
Canning and preserving: Fish, crabs, shrimps, oysters, and clams	Food preparations, not elsewhere specified	Sausage
Canning and preserving: Fruits and vegetables: pickles, jellies, preserves, and sauces	Fruits & vegetables, canned & preserved	Sausage casings—not made in meat-packing establishments
Cereal preparations	Fruits and vegetables, canning and preserving	Sausage, meat puddings, headcheese, etc., and sausage casings, not made in meat-packing establishments

Industry "Aggregate" and Census Industries Included		
Chewing gum	Hominy	Sausage, not made in slaughtering and meat-packing establishments
Coffee and spice, roasting and grinding	Ice cream	Sausages, prepared meats, and other meat products—not made in meat-packing establishments
Coffee and spices, ground	Ice cream and ices	Slaughtering and meat packing
Coffee and spices, roasted and ground	Lard, refined	Slaughtering and meat packing, not including retail butchering
Coffee essence of	Macaroni and vermicelli	Slaughtering and meat packing, wholesale
Coffee roasters	Macaroni, spaghetti, vermicelli, and noodles	Slaughtering and meat-packing, wholesale
Coffee roasting	Meat cured and packed (not specified)	Slaughtering, wholesale, not including meat packing
Confectionery	Meat packed beef	

Industry 2

Poultry dressing and packing, wholesale	Poultry killing, dressing, and packing, wholesale	Poultry, killing and dressing, not done in slaughtering and meatpacking establishments

Industry 3

Butter	Cheese	Condensed and evaporated milk
Butter, cheese, and condensed milk	Cheese, butter, and condensed milk	Creamery butter

Industry 4

Barley, pearl	Flour-mill and gristmill products	Rice flour
Flour and meal	Flouring and grist mill products	
Flour and other grain-mill products	Husks, prepared	

Industry 5

Rice cleaning	Rice cleaning and polishing	Rice, cleaning and polishing

Industry 6

Cane-sugar refining	Sugar and molasses refined cane	Sugar refining
Sugar and molasses	Sugar and molasses, refining	Sugar, refining, not including beet sugar

Industry "Aggregate" and Census Industries Included		
Sugar and molasses beet and grape	Sugar molds	
Industry 7		
Chocolate	Chocolate and cocoa products, not including confectionery	
Chocolate and cocoa products	Cocoa	
Industry 8		
Beverages	Mineral water	Water lime
Mineral and soda waters	Nonalcohclic beverages	
Industry 9		
Liquors bottled	Liquors vinous	Liquors, rectified or blended
Liquors distilled	Liquors wine	Liquors, vinous
Liquors malt	Liquors, distilled	Malt liquors
Liquors rectified	Liquors, malt	Wines
Industry 10		
Malt	Malt kilns	Small beer
Industry 11		
Baking and yeast powders	Baking powders, yeast, and other leavening compounds	Baking-powders
Baking powders and yeast	Baking, and yeast cakes and powders	Saleratus
Industry 12		
Oleomargarine	Oleomargarine and other butter substitutes	
Industry 13		
Glucose	Starch	Sugar and molasses sorghum
Industry 14		
Cordials and flavoring sirups	Flavoring extracts and flavoring sirups	Liquors cordials

Industry "Aggregate" and Census Industries Included		
Cordials and sirups	Flavoring extracts and flavoring sirups, not elsewhere classified	Molasses, refined
Flavoring extracts	Liquor-coloring	Sirups, other than sorghum

Industry 15

Cider	Vinegar
Cider refined	Vinegar and cider

Industry 16

Ice	Ice, (by patented process)	Ice, manufactured

Industry 17

Cigarettes	Tobacco and cigars chewing and smoking, and snuff	Tobacco, chewing, smoking, and snuff
Cigars	Tobacco and cigars cigars	Tobacco, cigars and cigarettes
Cigars and cigarettes	Tobacco and snuff	Tobacco, cigars, and cigarettes
Tobacco (chewing and smoking) and snuff	Tobacco manufactures	
Tobacco and cigars	Tobacco, chewing and smoking, and snuff	

Industry 18

Cotton braid, thread, lines, twine, and yarn	Cotton lamp-wick	Cotton thread, twine, and yarns
Cotton broad woven goods	Cotton mosquito-netting	Cotton yarn
Cotton flannel carding	Cotton narrow fabrics	Cotton, cleaning and rehandling
Cotton goods	Cotton pressing	Cotton, compressing
Cotton goods, (not specified)	Cotton small wares	Cotton, ginning
Cotton goods, including cotton small wares	Cotton table-cloths	Lace goods
Cotton lace	Cotton thread	

Industry 19

Combs	Miscellaneous fabricated products not elsewhere classified	Silk broad woven goods—contract factories

Industry "Aggregate" and Census Industries Included		
Combs and hairpins, not made from metal or rubber	Pins	Silk broad woven goods—regular factories or jobbers engaging contractors
Combs, shell and other	Rayon broad woven goods—contract factories	Silk goods
Fancy and miscellaneous articles, not elsewhere classified	Rayon broad woven goods—regular factories or jobbers engaging contractors	Silk goods (not specified)
Fancy articles	Rayon narrow fabrics	Silk goods sewing and twist
Fancy articles, not else where specified	Rayon throwing and spinning—contract factories	Silk narrow fabrics
Fancy articles, not elsewhere specified	Rayon yarn and thread, spun or thrown—regular factories or jobbers engaging contractors	Silk sewing and twist
Fans	Rules, ivory and wood	Silk throwing and spinning—contract factories
Ivory and bone work	Sewing birds	Theatrical scenery
Ivory work	Silk and fancy goods, fringes, and trimmings	Theatrical scenery and stage equipment
Ivory, shell, and bone work, not including buttons, combs, or hairpins	Silk and rayon manufactures	Turning ivory and bone
Ivory, shell, and bone work, not including combs and hairpins	Silk and silk goods	
Lamp shades	Silk and silk goods, including throwsters	

Industry 20

Artificial and preserved flowers and plants	Embroideries, other than Schiffli-machine products—contract factories	Millinery
Artificial feathers and flowers	Embroideries, other than Schiffli-machine products—made in regular factories or by jobbers engaging contractors	Millinery and dressmaking
Artificial feathers, flowers, and fruits	Embroideries: Schiffli-machine products	Millinery and lace goods
Artificial flowers	Embroidery	Millinery and lace goods, not elsewhere specified
Artificial flowers, feathers and plumes	Feathers and plumes	Millinery goods

Industry "Aggregate" and Census Industries Included		
Belting and hose, rubber	Feathers, cleaned, dressed, and dyed	Millinery, custom work
Belting and hose, woven and rubber	Feathers, plumes, and artificial flowers	Raincoats and other waterproof garments (except oiled cotton)
Belting and hose, woven, other than rubber	Feathers, plumes, and manufactures thereof	Robes, lounging garments, and dressing gowns
Bleaching straw-goods	Finishing of men's and boys' hats of fur-felt, wool-felt, and straw	Rubber and elastic goods
Boot and shoe findings	Flowers	Rubber goods other than tires, inner tubes, and boots and shoes
Boots and shoes, custom work and repairing	Fur hats	Rubber goods, not elsewhere specified
Boots and shoes, factory product	Furnishing goods, men's	Rubber products not elsewhere classified
Boots and shoes, not including rubber boots and shoes	Furnishing goods, men's not elsewhere classified	Rubber tires, tubes, and rubber goods, not elsewhere specified
Boots and shoes, rubber	Gloves and mittens	Shirts
Cap fronts	Gloves and mittens, cloth	Straw bonnet bleaching
Children's and infants' wear not elsewhere classified-made in inside factories or by jobbers engaging contractors	Gloves and mittens, leather	Straw goods
Children's coats-made in contract factories	Gutta-percha goods	Straw goods, not elsewhere specified
Children's coats-made in inside factories or by jobbers engaging contractors	Hair cloth	Suspenders
Children's dresses-made in contract factories	Hat and bonnet blocks	Suspenders, garters, and elastic woven goods
Children's dresses-made in inside factories or by jobbers engaging contractors	Hat and cap materials	Trimmings (not made in textile mills) and stamped art goods for embroidering
Clothing	Hat and cap materials, men's	Trimmings (not made in textile mills), stamped art goods, and art needlework—contract factories

Industry "Aggregate" and Census Industries Included		
Clothing (except work clothing), men's, youths', and boys', not elsewhere classified	Hat and cap materials; trimmings, etc	Trimmings (not made in textile mills), stamped art goods, and art needlework—made in regular factories or by jobbers engaging contractors
Clothing children's	Hat and cap, except felt and straw men's	Trousers (semidress), wash suits, and washable service apparel
Clothing ladies'	Hat bodies	Trusses, bandages, and supporters
Clothing men's	Hat materials	Women's and misses' blouses and waists—made in contract factories
Clothing men's, custom work and repairing	Hat tips	Women's and misses' blouses and waists—made in inside factories or by jobbers engaging contractors
Clothing men's, factory products	Hats and caps	Women's and misses' clothing, not elsewhere classfied—made in contract factories
Clothing men's, factory products buttonholes	Hats and caps, not including fur hats and wool hats	Women's and misses' clothing, not elsewhere classified—made in inside factories or by jobbers engaging contractors
Clothing women's	Hats and caps, other than felt, straw, and wool	Women's and misses' dresses (except house dresses)—made in contract factories
Clothing, leather and sheeplined	Hats, fur-felt	Women's and misses' dresses (except house dresses)—made in inside factories or by jobbers engaging contractors
Clothing, men's	Hats, straw	Women's, children's and infants' underwear and nightwear of cotton and flannelette woven fabrics
Clothing, men's, buttonholes	Hats, straw, men's	Women's, children's, and infants' underwear and nightwear of knitted fabrics

Industry "Aggregate" and Census Industries Included		
Clothing, men's, custom work and repairing	Hats, wool-felt	Women's, children's, and infants' underwear and nightwear of silk and rayon woven fabrics
Clothing, men's, factory product	Hatsand caps, not including wool hats	Women's, neckwear, scarfs, etc
Clothing, men's, factory product, buttonholes	Hatters' trimmings	Wool hats
Clothing, men's, including shirts	House dresses, uniforms, and aprons—made in contract factories	Wool scouring
Clothing, women's	House dresses, uniforms, and aprons—made in inside factories or by jobbers engaging contractors	Woolen and worsted goods
Clothing, women's, dressmaking	India-rubber and elastic goods	Woolen and worsted manufactures—contract factories
Clothing, women's, factory product	India-rubber goods	Woolen and worsted manufactures—regular factories or jobbers engaging contractors
Clothing, women's, not elsewhere classified	Leather gloves and mittens	Woolen goods
Clothing, work (including sheep-lined and blanket-lined work coats but not including shirts), men's	Men's and boys' hats and caps (except felt and straw)	Woolen yarn
Coats, suits, and skirts (except fur coats)-made in contract factories	Men's and boys' shirts (except work shirts), collars, and nightwear made in inside factories or by jobbers engaging contractors	Woolen, worsted, felt goods, and wool hats
Coats, suits, and skirts (except fur coats)-made in inside factories or by jobbers engaging contractors	Men's and boys' shirts (except work shirts), collars, and nightwear—made in contract factories	Work clothing (except work shirts), sport garments (except leather), and other men's and boys' apparel, not elsewhere classified
Collars and cuffs, men's	Men's and boys' suits, coats, and overcoats (except work clothing)—made in contract factories	Work gloves and mittens: cloth, cloth and leather combined

Industry "Aggregate" and Census Industries Included		
Collars and cuffs, paper	Men's and boys' suits, coats, and overcoats (except work clothing)—made in inside factories or by jobbers engaging contractors	Work shirts
Embroideries	Men's neckwear—made in inside factories or by jobbers engaging contractors	Worsted goods

Industry 21

Bleaching and dyeing	Dyeing and finishing cotton, rayon, silk, and linen textiles	Printing cotton and woolen goods
Calico-printing	Dyeing and finishing textiles	Satinet printing
Dyeing and bleaching	Dyeing and finishing textiles, exclusive of that done in textile mills	Whiting
Dyeing and cleaning	Dyeing and finishing woolen and worsted	

Industry 22

Hosiery	Hosiery—seamless	Knitted outerwear (except knit gloves)—contract factories
Hosiery and knit goods	Knit goods	Knitted outerwear (except knit gloves)—regular factories or jobbers engaging contractors
Hosiery—full-fashioned	Knitted cloth	Knitted underwear

Industry 23

Cloth sponging and miscellaneous special finishing	Cloth, sponging and refinishing	
Cloth sponging and refinishing	Cloth-finishing	

Industry 24

Carpets	Carpets rag	Mats and matting
Carpets and rugs, other than rag	Carpets, rag	Mats and rings

Industry "Aggregate" and Census Industries Included		
Carpets other than rag	Carpets, rugs, and mats made from such materials as paper fiber, glass, jute, flax, sisal, cotton, cocoa fiber, and rags	Mats and rugs

Industry 25

Oil floor cloth	Oil floor-cloth	Oilcloth, floor

Industry 26

Felting	Haircloth	

Industry 27

Batting, padding, and wadding: upholstery filling	Upholstering materials	Upholstery
Cotton batting and wadding	Upholstering materials, not elsewhere specified	Upholstery materials

Industry 28

Cotton waste	Processed waste and recovered wool fibers—regular factories or jobbers engaging contractors	Waste
Oakum	Shoddy	

Industry 29

Artificial leather and oilcloth	Oil cloth, silk	
Oil and enameled cloth	Oilcloth, enameled	

Industry 30

Bagging	Coach lace	Jute goods
Bagging, flax, hemp, and jute	Cordage	Jute goods (except felt)
Bags	Cordage and twine	Linen goods
Bags other than paper	Cordage and twine and jute and linen goods	Paper bags
Bags paper	Cotton bags	Paper bags, except those made in paper mills
Bags, other than paper	Cotton cordage	Textile bags—not made in textile mills

Industry “Aggregate” and Census Industries Included		
Bags, other than paper, not including bags made in textile mills	Filter bags	Thread, linen
Bags, other than paper, not made in textile mills	Flax and linen goods	Webbing
Bags, paper	Hemp hose	
Bags, paper, exclusive of those made in paper mills	Jute and jute goods	

Industry 31

Corsets	Hoop-skirts and corsets	
Corsets and allied garments	Skirt-supporters	

Industry 32

Bellows	Pocket-books	Trunks and valises
Belt clasps and slides	Pocket-books, portemonnaies, and wallets	Trunks carpet-bags, and valises
Belts (apparel), regardless of material	Pocketbooks, purses, and card cases	Trunks, suitcases, and bags
Belts, children’s	Razor-strops	Trunks, valises, and satchels
Leather goods	Saddlery and harness	Whips
Leather goods not elsewhere classified	Saddlery, harness, and whips	Whips and canes
Leather goods, not elsewhere classified	Small leather goods	Whips, whip-lashes, sockets, and canes
Leather goods, not elsewhere specified	Suitcases, brief cases, bags, trunks, and other luggage	Women’s pocketbooks, handbags, and purses
Pocketbooks	Trunk and carpet-bag frames	

Industry 33

Fur coats and other fur garments, accessories, and trimmings	Fur goods	

Industry 34

Aluminum manufactures	Curtains, draperies, and bedspreads—contract factories	Housefurnishings (except curtains, draperies, and bedspreads)

Industry "Aggregate" and Census Industries Included		
Aluminum products (including rolling and drawing and extruding), not elsewhere classified	Curtains, draperies, and bedspreads—made in regular factories or by jobbers engaging contractors	Mops and dusters
Cotton coverlets	House-furnishing goods, not elsewhere classified	Quilts
Curtains	House-furnishing goods, not elsewhere specified	

Industry 35

Awnings and tents	Awnings, tents, sails, and canvas covers	Sails
Awnings, tents, and sails	Canvas products (except bags)	

Industry 36

Clothing, horse	Military goods	Regalia and society banners and emblems
Flags and banners	Miscellaneous fabricated textile products not elsewhere classified	Regalia, and society badges and emblems
Flags, banners, regalia, society badges, and emblems	Nets and seines	Regalia, badges, and emblems
Horse covers	Nets, fish and seine	Regalias, banners, and flags

Industry 37

Logging camps and logging contractors (not operating sawmills)	Lumber staves, shooks, and headings	Timber cutting and timber hewed
Lumber and timber products	Lumber, sawed	Veneering
Lumber and timber products, not elsewhere classified	Sawmills, veneer mills, and cooperage-stock mills, including those combined with logging camps and with planing mills	Veneers
Lumber sawed	Shingles and lath	

Industry 38

Industry “Aggregate” and Census Industries Included		
Lumber planed	Planing-mill products (including general millwork), not made in planing mills connected with sawmills	Window blinds and shades
Lumber, planed	Sash, doors, and blinds	Window shades
Lumber, planing mill products, including sash, doors, and blinds	Venetian blinds	Window shades and fixtures
Lumber, planing-mill products, not including planing mills connected with sawmills	Window and door screens and weather strip	
Planing mills not operated in conjunction with sawmills	Window and door screens and weather strips	

Industry 39

Beds, spring	Mattresses and beds	Mattresses and spring beds
Mattresses and bed springs, not elsewhere classified	Mattresses and bedsprings	Mattresses and spring beds, not elsewhere specified

Industry 40

Furniture	Furniture, including store and office fixtures	Safes cheese
Furniture (not specified)	Household furniture, except upholstered	Safes provision
Furniture and refrigerators	Laboratory, hospital, and other professional furniture	Sewing machine cases
Furniture cabinet, school, and other	Medicine-chests	Show cases
Furniture chairs	Office furniture	Show-cases
Furniture iron bedsteads	Partitions, shelving, cabinet work, and office and store fixtures	Umbrella furniture
Furniture polish	Public-building furniture	Upholstered household furniture
Furniture refrigerators	Refrigerators	Upholstering
Furniture, chairs	Refrigerators and refrigerator cabinets, exclusive of mechanical refrigerating equipment	Upholstery
Furniture, factory products	Refrigerators and water-coolers	Whalebone and rattan

Industry "Aggregate" and Census Industries Included		
Furniture, including cabinet-making, repairing, and upholstering	Refrigerators, domestic (mechanical and absorption), refrigeration machinery and equipment, and complete air-conditioning units	

Industry 41

Baskets	Baskets, and rattan and willow ware	Whalebone and rattan, prepared
Baskets and rattan and willow ware, not including furniture	Rattan and willowware (except furniture) and baskets other than vegetable and fruit baskets	Willow furniture and willow ware
Baskets for fruits and vegetables	Whalebone and rattan	Willow ware

Industry 42

Boxes cigar	Boxes wooden tobacco	Boxes, cigar, wooden
Boxes tobacco	Boxes, cigar	Cigar boxes: wooden, part wooden

Industry 43

Boxes cheese	Boxes wooden packing	Boxes, wooden packing, except cigar boxes
Boxes fancy	Boxes, fancy and paper	Boxes, wooden, except cigar boxes
Boxes packing	Boxes, paper and other, not elsewhere specified	Fiber cans, tubes, and similar products
Boxes paper	Boxes, paper, not elsewhere classified	Paperboard containers and boxes not elsewhere classified
Boxes sugar	Boxes, wooden packing	Wooden boxes except cigar boxes

Industry 44

Carving	Skewers, wooden, for butchers & packers	Wood turned and shaped and other wooden goods, not elsewhere classified
Cooperage	Staves, heading, hoops, and shooks	Wood work, miscellaneous

Industry “Aggregate” and Census Industries Included		
Cooperage and wooden goods, not elsewhere specified	Truss hoops	Wood, turned and carved
Handles	Turning scroll-sawing, and molding	Wooden door-knobs
Handles, wooden	Wood brackets, moldings, and scrolls	Wooden goods, not elsewhere specified
Kindling wood	Wood products not elsewhere classified	Wooden ware
Kindling-wood	Wood pulp miscellaneous articles	Woodenware, not elsewhere specified
Oars	Wood pulp turned and carved	

Industry 45

Caskets, coffins, burial cases, and other morticians’ goods	Coffin trimmings	Coffins, burial cases, and undertakers’ goods
Coffin screws	Coffins	

Industry 46

Cork products	Cork-cutting	Life-preservers
Cork, cutting	Corks	

Industry 47

Matches		

Industry 48

Wood preserving		

Industry 49

Boot and shoe patterns	Lasts and boot-trees	
Lasts	Lasts and related products	

Industry 50

Looking-glass and picture frames	Mirror and picture frames	Mirror frames and picture frames

Industry 51

Industry "Aggregate" and Census Industries Included		
Card boards	Envelopes and cards, embossed	Paper writing
Card cutting	Greeting cards (except hand-painted)	Paper, printing and wrapping
Card cutting and designing	Paper	Paper, printing and writing
Cardboard	Paper (not specified)	Patterns and models
Cardboard, not made in paper mills	Paper and paperboard mills	Pencil cases
Cards enameled	Paper and wood pulp	Printing materials
Cards hand	Paper goods, not elsewhere classified	Pulp goods
Cards other than playing	Paper goods, not elsewhere specified	Show cards
Cards playing	Paper printing	Stationery goods, not elsewhere classified
Coated and glazed paper	Paper ruling	Stationery goods, not elsewhere specified
Converted paper products not elsewhere classified	Paper shades	Tags
Die-cut paper and paperboard, and converted cardboard	Paper staining	Tapes and binding
Envelopes	Paper wrapping	Valentines

Industry 52

Paper hangings	Wall paper	
Paper-hangings	Wall paper, not made in paper mills	

Industry 53

Book binding	Engraving, steel and copper plate, including plate printing	Paper patterns
Bookbinding and blank book making	Engraving, steel and copper-plate, and plate printing	Patterns and models
Bookbinding and blank books	Engraving, steel, including plate printing	Periodicals: publishing and printing
Bookbinding and blank-book making	Engraving, wood	Periodicals: publishing without printing
Bookbinding and related industries	General commercial (job) printing	Photo-engraving, not done in printing establishments

Industry "Aggregate" and Census Industries Included		
Books: printing without publishing	Gravure, rotogravure, and rotary photogravure (including preparation of plates)	Printing and publishing
Books: publishing and printing	Labels and tags	Printing and publishing (not specified)
Books: publishing without printing	Lithographing	Printing and publishing book
Charts, hydrographic	Lithographing and engraving	Printing and publishing job
Chromos and lithographs	Lithographing and photo-lithographing (including preparation of stones or plates and dry transfers)	Printing and publishing newspaper
Engraving	Lithography	Printing and publishing, book and job
Engraving (other than steel, copperplate, or wood), chasing, etching, and diesinking	Machine and hand typesetting (including advertisement typesetting)	Printing and publishing, music
Engraving (steel, copperplate, and wood); plate printing	Map mounting and coloring	Printing and publishing, newspaper and periodical
Engraving and diesinking	Maps	Printing and publishing, newspapers and periodicals
Engraving and die-sinking	Maps and atlases	Printing, tip
Engraving and stencil-cutting	Music-printing	Watch engraving
Engraving calico	Newspapers: publishing and printing	
Engraving on metal (except for printing purposes)	Newspapers: publishing without printing	

Industry 54

Photo-engraving	Photoengraving, not done in printing establishments (including preparation of plates)	
Photo-engraving, not done in printing establishments	Photolithographing and photoengraving	

Industry 55

Electrotyping and stereotyping, not done in printing establishments	Stereotyping and electrotyping	Stereotyping and electrotyping, not done in printing establishments

Industry 56

Bark ground	Dyestuffs and extracts—natural	Paints, varnishes, and lacquers
Bark sumac, and sumac prepared	Paint and varnish	Sumac, ground
Bark, ground	Paint-mills	Tanning materials, natural dyestuffs, mordants and assistants, and sizes
Colors and pigments	Paints	Tanning materials, natural dyestuffs, mordants, assistants, and sizes
Dye woods, stuffs, and extracts	Paints (not specified)	Varnish
Dye-woods and dye-stuffs	Paints and varnishes	Varnishes
Dyestuffs and extracts	Paints lead and zinc	White-lead

Industry 57

Cottonseed oil, cake, meal, and linters	Oil linseed	Oil, essential
Lard, refined	Oil neatsfoot	Oil, lard
Oil Resin	Oil vegetable (not specified)	Oil, linseed
Oil and cake, cottonseed	Oil vegetable castor	Oil, lubricating
Oil animal	Oil vegetable cotton-seed	Oil, not elsewhere specified
Oil castor	Oil vegetable essential	Oil, resin
Oil cocoa-nut	Oil vegetable linseed	Oils essential
Oil cotton-seed	Oil water	Soybean oil, cake, and meal
Oil fish	Oil, cake, and meal, cottonseed	Vegetable and animal oils, not elsewhere classified
Oil fish, whale and other	Oil, cottonseed and cake	
Oil lard	Oil, cottonseed, cake	

Industry 58

Acid pyroligneous	Compressed and liquefied gases—not made in petroleum refineries or in natural-gasoline plants	Patent medicines and compounds
Acid sulphuric	Drug grinding	Patent medicines and compounds and druggists' preparations

Industry "Aggregate" and Census Industries Included		
Alcohol	Druggists' preparations	Patent or proprietary medicines and compounds
Barilla	Druggists' preparations, not including prescriptions	Pitch, brewers' and Burgundy
Celluloid and celluloid goods	Druggists' proparations	Sulphur
Chemicals	Drugs and chemicals	Tar and turpentine
Chemicals bichromate of potash	Drugs and medicines (including drug grinding)	Turpentine and rosin
Chemicals not elsewhere classified	Drugs, ground	Turpentine crude
Chemicals, not elsewhere classified	Gum and gum cleaning	Turpentine distilled
Coal-oil, refined	Lye, condensed	Zinc oxide of
Coal-tar products	Medicines, extracts and drugs	
Compressed and liquefied gases	Oil, illuminating, not including petroleum refining	

Industry 59

Perfumery and cosmetics	Perfumery, cosmetics, and fancy soaps	
Perfumery and fancy soaps	Perfumes, cosmetics, and other toilet preparations	

Industry 60

Blacking and water-proof composition	Insecticides, fungicides, and related industrial and household chemical compounds	

Industry 61

Candle adamantine	Candles, adamantine and wax	Soap and candles
Candle wax	Salt	Soap and glycerin
Candles	Soap	Wax-work

Industry 62

Bee-hives	Charcoal pulverized	Granular fuel
Charcoal	Coke	Oven coke and coke-oven byproducts

Industry "Aggregate" and Census Industries Included		
Charcoal and coke	Coke, not including gas-house coke	

Industry 63

Ashes, pot and pearl	Fertilizers	Fertilizers, (not plaster, ground)

Industry 64

Explosives and fireworks	Gunpowder	Saltpeter
Fireworks	High explosives	Torpedoes
Fire-works	Salpeter and nitrate of soda	

Industry 65

Salt	Salt ground	

Industry 66

Bone black	Ivory-black	Lamp-black
Bone, ivory, and lamp black	Lampblack	

Industry 67

Ink	Ink writing	Ink, writing
Ink printing	Ink, printing	Printing ink

Industry 68

Ammunition	Ammunition, cartridges	

Industry 69

Blacking	Cleaning and polishing preparations	Polishing preparations
Blacking and cleansing and polishing preparations	Cleaning and polishing preparations, blackings, and dressings	Stove-polish
Blacking, stains, and dressings	Cleansing and polishing preparations	

Industry 70

Industry “Aggregate” and Census Industries Included		
Glue	Glue, not elsewhere specified	
Glue and gelatin	Isinglass	

Industry 71

Bone boiling	Grease and tallow (except lubricating greases)	Hides and tallow
Grease	Grease and tallow, not including lubricating greases	
Grease and tallow	Greaso and tallow	

Industry 72

Axle grease	Gas, illuminating and heating	Oil kerosene
Benzoline	Lubricating greases	Oil lubricating
Camphene and burning-fluid	Lubricating oils and greases, not made in petroleum refineries	Petroleum refining
Gas	Lubricating oils and greases—not made in petroleum refineries	Petroleum, refining
Gas illuminating	Oil coal	

Industry 73

Blueing	Bluing	Washing blue

Industry 74

Mucilage and paste	Mucilage, paste, and other adhesives, except glue and rubber cement	
Mucilage, paste and other adhesives, not elsewhere specified	Putty	

Industry 75

Wallboard and wall plaster (except gypsum), building insulation (except mineral wool), and floor composition		

Industry "Aggregate" and Census Industries Included		
Industry 76		
Asphaltum work	Paving materials	Paving-materials
Paving and paving materials	Paving materials: Asphalt, tar, crushed slag, and mixtures	Paying blocks and paying mixtures: asphalt, creosoted wood, and composition
Industry 77		
Alloying; and rolling and drawing of nonferrous metals, except aluminum	Foundry and machineshop products	Paper-mill, pulp-mill, and paper-products machinery
Artificial eyes	Foundry supplies	Pencils (except mechanical) and crayons
Artificial limbs	Furnaces, ranges, registers, and ventilators	Pencils lead
Artists' materials	Gas and electric fixtures	Pencils, lead (including mechanical)
Automotive elcetrical equipment	Gas and electric fixtures, lamps and reflectors	Penholders, wooden
Babbitt metal and solder	Gas and electric fixtures; lamps, lanterns, and reflectors	Pens and pencils gold
Batteries, storage and primary (dry and wet)	Gas and lamp fixtures	Pens and pencils steel
Beauty-shop and barber-shop equipment	Gas fixtures, lamps, and chandeliers	Pens, fountain and stylographic
Bells	Gas machines and gas and water meters	Pens, fountain and stylographic; pen points, gold, steel, and brass
Blacksmiths' tools	Gas machines and meters	Pens, fountain, stylographic and gold
Blocks, pumps and spars	Gas machines, gas meters, and water and other liquid meters	Pens, gold
Blocks, pumps, and spars	Gasometers	Pens, mechanical pencils, and pen points
Blowers; exhaust and ventilating fans	Gasometers and tanks	Phonographs
Bookbinders' machinery	Generating, distribution, and industrial apparatus, and apparatus for incorporation in manufactured products, not elsewhere classified	Phonographs and graphophones

Industry "Aggregate" and Census Industries Included		
Brass and German silver, rolled	Globes, terrestrial and celestial	Plated and britannia ware
Brass and bell founding	Gold and silver assaying and refining	Plated ware
Brass and bronze products	Gold and silver, reduced and refined	Printers' chases, furniture, and rollers
Brass and copper tubing	Gold and silver, reducing and refining, not from the ore	Printers' fixtures
Brass and copper, rolled	Gold, silver, and platinum, reducing and refining, not from the ore	Printing lithographic presses
Brass and copper-tubing	Hair jewelry	Printing materials
Brass book clasps and badges	Hatters' tools	Printing materials, not including type or ink
Brass castings and brass finishing	Hoisting apparatus and machines	Printing-trades machinery and equipment
Brass founding and brass ware	Industrial machinery, not elsewhere classified	Professional and scientific instruments (except surgical and dental)
Brass founding and finishing	Instruments	Pumping equipment and air compressors
Brass ornaments	Instruments, professional and scientific	Pumps
Brass rolled	Iron forged, rolled, and wrought	Pumps (hand and power) and pumping equipment
Brass ware	Jewelers' dies, tools, and machinery	Pumps, not including power pumps
Brass wire and wire cloth	Jewelers' findings and materials	Pumps, not including steam pumps
Brass, bronze, and copper products	Jewelry	Pumps, steam and other power
Brassware	Jewelry (not specified)	Radios, radio tubes, and phonographs
Brick machinery and tools	Jewelry (precious metals)	Registers, cash
Bronze castings	Lamp tixtures	Roofing and roofing materials
Bronze powders	Lamp trimmings	Roofing materials
Calcium lights	Lamps	Roofing, built-up and roll; asphalt shingles; roof coating (except paint)
Calcium-lights	Lamps and reflectors	Roofing, built-up and roll; asphalt shingles; roof coatings other than paint

Industry "Aggregate" and Census Industries Included		
Carpenters' tools	Lamps, lanterns, & locomotive head-lights	Roofing-materials
Cars and trucks, industrial	Lead bar and sheet	Rooting
Cash registers and calculating machines	Lead manufactures of	Seal and copying presses
Chalk and crayons	Lead pigs	Secondary smelting and refining of nonferrous metals, not elsewhere classified
Churns	Lead pipe	Secondary smelting and refining, gold, silver, and platinum
Coffins and burial cases, trimming and finishing	Lead shot	Sheet-metal work not specifically classified
Coffins, burial cases, and undertakers' goods	Lead, bar, pipe and sheet	Shoemakers tools
Commercial laundry, dry-cleaning, and pressing machinery	Lead, bar, pipe, and sheet	Silver manufactures of
Communication equipment	Lead, smelting and refining	Silver plated and Britannia ware
Construction and similar machinery (except mining and oil-field machinery and tools)	Lighting fixtures	Silversmithing
Cooper, tin, and sheet-iron work	Lightning rods	Silversmithing and silverware
Coopers' tools	Lightning-rods	Silverware
Copper and brass ware	Machine tools	Silverware and plated ware
Copper milled and smelted	Machine-shop products not elsewhere classified	Smelting and refining, not from the ore
Copper rolled	Machine-shop repairs	Speaking-tubes
Copper sheet and bolt	Machine-tool accessories and small metal-working tools, not elsewhere classified	Special industry machinery, not elsewhere classified
Copper smelting	Machine-tool and other metalworking-machinery accessories, metalcutting and shaping tools, and machinists' precision tools	Spectacles and eye-glasses
Copper work	Machinery (not specified)	Spectacles and eyeglasses
Copper, smelting and refining	Machinery fire-engines	Stationery
Copper, tin, and sheet-iron products	Machinery railroad repairing	Sulphuric, nitric, and mixed acids

Industry "Aggregate" and Census Industries Included		
Copper, tin, and sheet-iron work, including galvanizediron work, not elsewhere classified	Machinery shingle-machines	Surgical and medical instruments
Coppersmithing	Machinery steam engines and boilers	Surgical and orthopedic appliances, including artificial limbs
Costume jewelry and costume novelties (jewelry other than fine jewelry)	Machinery steam-engines, &c	Surgical appliances
Cotton gins	Machinery turbine water-wheels	Surgical appliances and artificial limbs
Curriers' tools	Machinery wood-working	Surgical supplies and equipment not elsewhere classified; orthopedic appliances
Cutlery	Machinists' tools	Teeth, porcelain
Cutlery and tools, not elsewhere specified	Measuring instruments, mechanical (except electrical measuring instruments, watches, and clocks)	Telegraph and telephone apparatus
Dental equipment and supplies	Mechanical power-transmission equipment	Tin cans and other tinware not elsewhere classified
Dental goods	Metal repaired and white	Tin cans and other tinware, not elsewhere classified
Dental goods and equipment	Metal spinning	Tin copper, and sheet-iron ware
Dentistry, mechanical	Metal type	Tin, copper, and sheet-iron ware
Dentists' materials	Metal working machinery and equipment, not elsewhere classified	Tinners' tools and machines
Dumb-waiters	Meters gas	Tinsmithing, coppersmithing, and sheet-iron working
Eave-troughs	Meters gas and water	Tinware, not elsewhere specified
Electric lamps	Meters water	Tools, not elsewhere specified
Electric light and power	Mining machinery and equipment	Typewriters and supplies
Electrical apparatus and supplies	Money-drawers	Vault lights and ventilators
Electrical appliances	Newspaper-directing machines	Vault lights, (of iron and glass)
Electrical machinery, apparatus, and supplies	Nickel, smelted	Vault-lights

Industry "Aggregate" and Census Industries Included		
Electrical products not elsewhere classified	Nonferrous-metal alloys and products, not including aluminum products	Vending, amusement, and other coin-operated machines
Electro-magnetic machines	Nonferrous-metal foundries (except aluminum)	Windlasses
Elevators, escalators, and conveyors	Nonferrous-metal products not elsewhere classified	Windmills
Engines, steam, gas, and water	Office and store machines, not elsewhere classified	Wire insulated
Engravers materials	Oil tanks	Wiring devices and supplies
Engravers' blocks and wood	Oil-field machinery and tools	Woodworking machinery
Engravers' materials	Ophthalmic goods: lenses and fittings	X-ray and therapeutic apparatus and electronic tubes
Food-products machinery	Optical goods	Zinc
Foundery-facings	Optical instruments and lenses	Zinc smelted and rolled
Foundry and machine shop products	Ornaments paper	Zinc statuary and building ornaments
Foundry and machine-shop products	Ornaments plaster	
Foundry and machine-shop products, not elsewhere classified	Ornaments terra-cotta	

Industry 78

Tin and terne plate

Industry 79

Tinfoil

Industry 80

Leather	Leather patent and enameled leather	Leather, tanned, curried, and finished
Leather curried	Leather skin-dressing	Leather: Tanned, curried, and finished
Leather dressed skins	Leather tanned	Leather: tanned, curried, and finished—contract factories
Leather morocco	Leather, curried	Leather: tanned, curried, and finished-regular factories or jobbers engaging contractors

Industry “Aggregate” and Census Industries Included		
Leather morocco, tanned and curried	Leather, dressed skins	Leather-board
Leather patent and enameled	Leather, tanned	

Industry 81

Belting and hose, (leather)	Belting, leather	Leather belting and hose
Belting and hose, leather	Industrial leather belting and packing leather	

Industry 82

Boot and shoe cut stock	Boot and shoe findings, not made in boot and shoe factories	Boots and shoes, other than rubber
Boot and shoe cut stock and findings	Boot and shoe uppers	Footwear (except rubber)
Boot and shoe cut stock, exclusive of that produced in boot and shoe factories	Boots and shoes	Shoe findings
Boot and shoe cut stock, not made in boot and shoe factories	Boots and shoes, custom work and repairing	Shoe peg machines
Boot and shoe findings	Boots and shoes, including cut stock and findings	Shoe-pegs
Boot and shoe findings, exclusive of those produced in boot and shoe factories	Boots and shoes, not including rubber boots and shoes	

Industry 83

Aquariums	Glass products (except mirrors) made from purchased glass	Looking-glasses
Glass	Glass stained	Mirrors
Glass containers	Glass ware, (not specified)	Mirrors and other glass products made of purchased glass
Glass cut	Glass window	Mirrors, framed and unframed
Glass plate	Glass, cutting, staining, and ornamenting	Mirrors, framed and unframed, not elsewhere specified

Industry 84

Type and type and stereotype founding	Type founding	Type founding and printing materials

Industry 85

Artificial stone	Concrete products	Porcelain ware
Artificial stone products	Conerete products	Pottery
Bath-tubs	Crucibles	Pottery and stoneware
Brick	Drain and sewer pipe	Pottery, including porcelain ware
Brick and hollow structural tile	Drain tile	Pottery, terra cotta, and fire-clay products
Brick and tile	Drain-pipe	Pottery, terra-cotta and fire-clay products
Brick and tile, terra-cotta, and fireclay products	Fire brick	Rooting
Building-stone, artificial	Floor and wall tile (except quarry tile)	Stone and earthen ware
Cement	Lime	Stone- and earthen-ware
Cement pipe	Lime and cement	Stucco and stucco work
Cisterns	Masonry, brick and stone	Terra-cotta ware
Clay products (other than pottery) and nonclay refractories	Porcelain electrical supplies	Water closets

Industry 86

China and glass decorating	China decorating, not including that done in potteries	China firing and decorating, not done in potteries
China decorating	China firing and decorating (for the trade)	

Industry 87

Gypsum products	Plaster, ground	Wall plaster and composition flooring
Plaster and manufactures of	Wall plaster	Wall plaster, wall board, insulating board, and floor composition

Industry 88

Mantels, slate, marble, and marbleized	Monuments and tombstones	Soap-stone stoves, fire-places, sinks, and cisterns

Industry "Aggregate" and Census Industries Included		
Marble and stone work	Monuments, tombstones, cut-stone, and stone products not elsewhere classified	Statuary and art goods
Marble and stone work, (not specified)	School apparatus	Statuary and art goods (except stone and concrete)—factory production
Marble monuments and tomb-stones	School slates and slate pencils	Statuary and art goods, factory product
Marble, granite, slate, and other stone products	Soap stone	Well curbs

Industry 89

Abrasive wheels, stones, paper, cloth, and related products	Grindstones	Sand paper
Emery and other abrasive wheels	Grindstones and grindstone quarrying	Seythe rifles stones
Emery wheels	Hones and whetstones	
Emery wheels and other abra-sive and polishing appliances	Sand and emery paper and cloth	

Industry 90

Asbestos products, not includ-ing steam packing	Steam and other packing; pipe and boiler covering	
Steam and other packing, pipe and boiler covering, and gas-kets, not elsewhere classified	Steam packing	

Industry 91

Barytes	Emery reduced and ground	Minerals and earths, ground or otherwise treated
Chalk prepared	Glass sand	Quartz, milled
Corundum	Kaolin and ground earths	
Emery	Kaolin and other earth grinding	

Industry 92

Blast-furnace products	Iron and steel, processed	Iron forged, rolled, and wrought

Industry "Aggregate" and Census Industries Included		
Cast-iron pipe	Iron and steel, steel works and rolling mills	Iron pigs
Cast-iron pipe and fittings	Iron and steel, tempering and welding	Steel (not specified)
Gray-iron and semisteel castings	Iron and steel: Steel works and rolling mills	Steel Bessemer
Iron and steel	Iron blooms	Steel cast
Iron and steel, blast furnaces	Iron cast	Steel castings
Iron and steel, bolts, nuts, washers, and rivets, not made in steel works or rolling mills	Iron castings (not specified)	Steel works and rolling mills
Iron and steel, cast-iron pipe	Iron forged and rolled	Steel, and manufactures of

Industry 93

Wire	Wire, drawn from purchased bars or rods	
Wire drawn from purchased rods	Wired steel	

Industry 94

Horse shoe nails	Iron nails and spikes, cut and wrought	
Iron and steel, nails and spikes, cut and wrought, including wire nails	Nails, cut, wrought, and spikes	

Industry 95

Iron forged, rolled, and wrought	Wire work	Wirework, including wire rope and cable
Wire cloth	Wire work, sieves, and bird-cages	Wirework, not elsewhere classified
Wire rope	Wirework not elsewhere classified	Wirework, not elsewhere specified

Industry 96

Cutlery	Cutlery and edge tools	Mowing-machine knives

Industry "Aggregate" and Census Industries Included		
Cutlery (except aluminum, silver, and plated cutlery) and edge tools	Cutlery and edge-tools, (not specified)	Scythes
Cutlery (not including silver and plated cutlery) and edge tools	Edge-tools and axes	Stone-cutters' tools

Industry 97

Anvils and vises	Shovels, spades, forks, and hoes	Tools, not including edge tools, machine tools, files, or saws
Handspikes	Tools (except edge tools, machine tools, files, and saws)	
Shovels and spades	Tools, not elsewhere specified	

Industry 98

Files

Industry 99

Saws

Industry 100

Bank locks	Hardware not elsewhere classified	Hardware, saddlery
Hardware	Hardware saddlery	Hinges, wrought and cast

Industry 101

Enameled-iron sanitary ware and other plumbers' supplies (not including pipe and vitreous and semivitreous china sanitary ware)	Plumbers supplies
Plumbers materials	Plumbers' supplies, not including pipe or vitreous-china sanitary ware

Industry 102

Industry "Aggregate" and Census Industries Included		
Furnaces, ranges, registers, and ventilators	Oil burners, domestic and industrial	Steam water-gauges
Gas and oil stoves	Steam and gas fittings and valves	Stoves and furnaces, in cluding gas and oil stoves
Heating and cooking apparatus, except electric, not elsewhere classified	Steam fittings and heating apparatus	Stoves and hot-air furnaces
Heating-apparatus	Steam fittings and steam and hot-water heating apparatus	Stoves and ranges (other than electric) and warm-air furnaces
Iron cast	Steam fittings, regardless of material	Stoves, gas and oil
Iron castings stoves, heaters, & hollow ware	Steam heaters and heating apparatus	Stoves, ranges, water heaters, and hot-air furnaces (except electric)

Industry 103

Power boilers and associated products		

Industry 104

Automobile stampings	Iron, enameled	Stamped and pressed metal products (except automobile stampings)
Enameling	Japanned ware	Stamped ware
Enameling and enameled goods	Japanning	Stamped ware, enameled ware, and metal stamping, enameling, japanning, and lacquering
Enameling and japanning	Metallic caps and labels	Tinned iron ware
Enameling, japanning, and lacquering	Stamped and enameled ware, not elsewhere specified	

Industry 105

Galvanizing	Galvanizing and other coating—carried on in plants not operated in connection with rolling mills	
Galvanizing and other coating processes	Iron, galvanized	

Industry 106

Bridge-building	Iron forged, rolled, and wrought	Structural and ornamental iron and steel work, not made in plants operated in connection with rolling mills
Bridges	Iron railing, wrought	Structural ironwork, not made in steel works or rolling mills
Fabricated structural steel and ornamental metal work, made in plants not operated in connection with rolling mills	Ironwork, architectural and ornamental	Vanes, weather
Fire escapes	Stair building	
Grates and fenders	Stair rods	

Industry 107

Doors, shutters, and window sash and frames, metal	Iron forged, rolled, and wrought	Sash, doors, and blinds
Doors, window sash, frames, molding, and trim (made of metal)	Sash doors and blinds	
Iron and steel, doors and shutters	Sash metal	

Industry 108

Bolts, nuts, washers, and rivets	Bolts, nuts, washers, and rivets-made in plants not operated in connection with rolling mills	Iron and steel, bolts, nuts, washers, and rivets, not made in rolling mills
Bolts, nuts, washers, and rivets, not made in plants operated in connection with rolling mills	Iron and steel, bolts, nuts, washers, and rivets	Iron bolts, nuts, washers, and rivets

Industry 109

Anchors and chains	Horse shoes	Iron and steel, wrought pipe
Axles	Iron anchors and cable chains	Iron forged, rolled, and wrought

Industry "Aggregate" and Census Industries Included		
Forgings, iron and steel, not made in plants operated in connection with rolling mills	Iron and steel forgings, not made in steel works or rolling mills	Steel forged
Forgings, iron and steel—made in plants not operated in connection with rolling mills	Iron and steel, forgings	Whitesmithing

Industry 110

Iron and steel, pipe, wrought	Iron forged, rolled, and wrought	Iron pipe, wrought

Industry 111

Springs, car, carriage, locomotive, and other	Springs, steel, car and carriage	Springs, steel, except wire, not made in plants operated in connection with rolling mills
Springs, steel (except wire)—made in plants not operated in connection with rolling mills	Springs, steel, car and carriage, not made in steel works or rolling mills	Steel springs

Industry 112

Screw-machine products and wood screws	Screws, machine	
Screws	Wooden screws	

Industry 113

Keys, metallic	Steel barrels, kegs, and drums	
Steel barrels, drums and tanks, portable	Vats	

Industry 114

Fire arms	Gun locks and materials	Powder-flasks and percussion-caps
Firearms	Gunsmithing	
Fire-arms	Percussion-caps	

Industry 115

Industry "Aggregate" and Census Industries Included		
Safes and vaults	Safes fire-proof	Sates, doors, and vaults, (fire-proof)

Industry 116

Clock materials	Watch and clock materials and parts, except watchcases	Watches
Clocks	Watch and clock materials, except watchcases	Watches, watch repairing, and materials
Clocks and watches, including cases and materials	Watch guards	
Watch and clock materials	Watch materials	

Industry 117

Clock cases	Watch cases
Clock-cases	Watchcases

Industry 118

Glaziers' diamonds	Lapidary work
Lapidaries' work	Pearl goods

Industry 119

Electroplating	Electroplating, plating, and polishing

Industry 120

Gold and silver leaf and foil	Gold and silver, leaf and foil	Gold leaf and foil

Industry 121

Tin foil

Industry 122

Agricultural implements	Agricultural implements miscellaneous	Agricultural machinery (except tractors)
Agricultural implements fanning-mills	Agricultural implements mowing and reaping machines	Clover hulling

Industry "Aggregate" and Census Industries Included		
Agricultural implements grain-cradles and seythe-snaths	Agricultural implements plows, harrows, and cultivators	Hay-pressing
Agricultural implements grain-drills	Agricultural implements rakes	Machinery hay and cotton presses
Agricultural implements handles, plow, and other	Agricultural implements straw-cutters	
Agricultural implements hoes	Agricultural implements thrashers, horse-powers, and separators	

Industry 123

Confectioners' tools	Machinery ribbon-looms	Textile machinery and parts
Machinery cotton and woolen	Textile machinery	

Industry 124

Scales and balances

Industry 125

Sad-irons	Washing machines and clothes-dryers
Washing machines and clothes wringers	Washing-machines and clothes-wringers

Industry 126

Sewing machine needles	Sewing machines and attachments	Sewing-machine fixtures
Sewing machine shuttles	Sewing machines, cases, and attachments	Sewing-machines
Sewing machines	Sewing-machine cases	

Industry 127

Automobile bodies and parts	Carriage-trimmings	Hubs, spokes, bows, shafts, wheels, & felloes
Automobile trailers (for attachment to passenger cars)	Carriages	Motor vehicles, motor-vehicle bodies, parts and accessories
Automobiles	Carriages and sleds, children's	Motor vehicles, not including motorcycles

Industry "Aggregate" and Census Industries Included		
Automobiles, including bodies and parts	Carriages and wagons	Motor-vehicle bodies and motor-vehicle parts
Bicycles and tricycles	Carriages and wagons and materials	Motorcycles, bicycles and parts
Bicycles, motorcycles, and parts	Carriages and wagons, including repairs	Spokes, hubs, felloes, shafts, and bows
Carriage and wagon materials	Carriages wagons	Steering apparatus
Carriage trimmings	Carriagesmithing	Wheelbarrows
Carriage, wagon, sleigh, and sled materials	Fire engines	

Industry 128

Car and general construction and repairs, steam-railroad repair shops	Cars and general shop construction and repairs by steam-railroad companies	Cars, railroad and street, and repairs, not including establishments operated by steam railroad companies
Car brakes	Cars and general shop construction and repairs by street-railroad companies	Cars, steam-railroad, not including operations of railroad companies
Car fixtures and trimmings	Cars, electric and steam railroad, not built in railroad repair shops	Cars, street-railroad, not including operations of railroad companies
Car linings	Cars, electric-railroad, not including operations of railroad companies	Car-wheels
Cars and car equipments-railroad, street, and rapid-transit	Cars, omnibuses, and repairing	Locomotive engines and repairing
Cars and general shop construction and repairs by steam railroad companies	Cars, railroad and repairs	

Industry 129

Aircraft and parts	Aircraft and parts, including aircraft engines	

Industry 130

Blocks and spars	Masts and spars	Shipbuilding and ship repairing

Industry "Aggregate" and Census Industries Included		
Blocks, pumps, and spars	Rigging	Shipbuilding, including boat building
Boat building and boat repairing	Ship and boat building	Shipbuilding, iron and steel
Boats	Ship and boat building, steel and wooden, including repair work	Shipbuilding, steel
Iron ship-building and marine engines	Ship and boat building, wooden	Shipbuilding, wooden, including boat building
Iron steamships	Ship building, ship materials, & repairs	
Mast hoops and hanks	Shipbuilding	

Industry 131

Cameras	Photographic apparatus and materials	Photographic materials
Photographic apparatus	Photographic apparatus and materials and projection equipment (except lenses)	Photographs

Industry 132

Muscial instruments: Organs	Musical instruments miscellaneous	Musical instruments, piano and organ materials
Musical instrument parts and materials: Piano and organ	Musical instruments organs	Musical instruments, pianos
Musical instruments (not specified)	Musical instruments organs and materials	Musical instruments, pianos and materials
Musical instruments and materials, not specified	Musical instruments pianofortes	Musical instruments, pianos and organs and materials
Musical instruments and parts and materials, not elsewhere classified	Musical instruments pianos and materials	Musical instruments: Pianos
Musical instruments materials	Musical instruments, organs	Organs
Musical instruments melodeous	Musical instruments, organs and materials	Piano-forte stools
Musical instruments melodeous, house-organs, and materials	Musical instruments, parts, and materials not elsewhere classified	

Industry “Aggregate” and Census Industries Included

Industry 133

Carriages and sleds, children’s	Games and toys (except dolls and children’s vehicles)	Toys and games
Carriages children’s	Toy books and games	Toys tin
Children’s vehicles	Toys	Wagons and carts
Dolls (except rubber)	Toys (not including children’s wheel goods or sleds), games, and playground equipment	

Industry 134

Base-ball goods	Billiard tables, bowling alleys, and accessories	Sporting and athletic good not else Where classified
Billiard & bagatelle tables, cues & materials	Croquet sets	Sporting and athletic goods
Billiard and bagatelle tables	Fish-hooks	Sporting and athletic goods, not including firearms or ammunition
Billiard and pool tables, bowling alleys, and accessories	Fishing lines, nets, and tackle	Sporting goods
Billiard cues	Fly-nets	
Billiard tables and materials	Hunting and fishing tackle	

Industry 135

Hand stamps	Hand stamps, stencils and brands	Hand-stamps
Hand stamps and stencils and brands	Hand stamps, stencils, and brands	Stencils and brands

Industry 136

Carbon paper and inked ribbons		

Industry 137

Buttons		

Industry 138

Industry "Aggregate" and Census Industries Included		
Jewelry and instrument cases	Jewelry cases and instrument cases	
Jewelry boxes and cases	Stereoscopic cases	

Industry 139

Brooms	Brush blocks	Brushes, (not whisk)
Brooms and brushes	Brush handles and stocks	Brushes, other than rubber
Brooms and whisk-brushes	Brushes	Carpet sweepers

Industry 140

Furs	Furs, dressed	Furs, dressed and dyed

Industry 141

Signs	Signs and advertising novelties	Signs, advertising displays, and advertising novelties

Industry 142

Fabricated plastic products, not elsewhere classified		

Industry 143

Umbrellas and canes	Umbrellas and parasols	Umbrellas, parasols, and canes

Industry 144

Pipe tongs	Pipes meerschaums	
Pipes (tobacco)	Pipes, tobacco	

Industry 145

Mineral water water apparatus	Soda water apparatus	Soda-water apparatus

Industry 146

Bottle molds	Models and patterns	Models and patterns, not including paper patterns
Candle-molds	Models and patterns (except paper patterns)	

Industry "Aggregate" and Census Industries Included		
	Industry 147	
Hair work	Hairwork	Wigs and hair-work
	Industry 148	
Wool carding and cloth-dressing	Wool pulling	
Wool cleaning and pulling	Wool-carding and cloth-dressing	
	Industry 149	
Hooks and eyes	Needles and pins	Needles, pins, hooks and eyes, and slide and snap fasteners
Needles	Needles, pins, and hooks and eyes	Needle-threaders
	Industry 150	
Fire extinguishers, chemical		

C.4 Right Hand Side Variables

For most census years, literacy rates and associated variables come from IPUMS microdata (Ruggles et al., 2010). However, no microdata exist for 1890. To address this, we entered the 1890 census tabulations of the size of the literate and total population by city and state (page lvi and xxxiii, respectively of U.S. Department of Interior, United States Census Office, 1897). For areas not covered by the list of tabulated cities, we use the state residual literacy rate. That is, we take the state totals and subtract off the totals in all of the cities we observe, and assign the residual literacy rate to each of the counties we do not have data on.

U.S. Department of Interior, United States Census Office (1897) is also the source for the number of foreign-born by country of origin in 1890, used in the construction of the instrument (page lxxii). The instrument relies on the interaction of county shares by origin in a base year – we use 1850 and 1880 – and the national stocks of by origin and literacy. The stocks and literacy rates of each origin group – with U.S. natives shown for comparison is shown in Table C.7. (The table is in descending order of the simple average of the size of the group across all years in the data.) The instrument uses the separate national stocks of literate and illiterates by origin, which can be calculated from the product of the literacy rates (or 1-literacy rate for illiterate stock) and the total stock shown above. The stocks in the 1890 table we use are not broken out by literacy, so we impute the literacy rate in 1890 of each origin group by taking the average of the 1880 and 1900 observed rates of literacy for each origin group (shown in Table C.7).

In the actual construction of the instrument, natives are further subdivided into their "origins" – states of birth (not shown in table). The size of the native literate and illiterate population from each state of birth is imputed as the average of the 1880 and 1900 values.

Table C.7. Population Stocks and Literacy Shares, by Origin and Year

	Stocks				Share Literate			
Origin	1860	1880	1900	1920	1860	1880	1900	1920
US-Born	12725000	29491710	40521900	58119000	0.73	0.76	0.89	0.95
German	1128500	1889690	2632900	1587800	0.88	0.95	0.93	0.96
Irish	1518600	1861140	1647060	1005800	0.74	0.80	0.88	0.97
Russian/Polish	10000	80390	700440	2667900	0.85	0.79	0.70	0.79
Canadian	194600	633690	1148700	1126000	0.70	0.84	0.89	0.95
English	398700	629030	831680	785600	0.87	0.95	0.97	0.99
Italian	10000	46550	418900	1491100	0.89	0.67	0.53	0.68
Swedish	17300	178500	589980	604800	0.82	0.91	0.94	0.97
Austrian	8200	33610	258760	556500	0.91	0.92	0.72	0.81
Norwegian	33400	169840	343600	352900	0.81	0.86	0.92	0.96
Scottish	97500	161270	232880	255000	0.91	0.96	0.98	0.99
Mexican	24300	114440	86640	391100	0.47	0.39	0.38	0.57
Hungarian	900	9610	129860	344000	1.00	0.90	0.71	0.86
Czech	10300	76570	153400	372200	0.76	0.88	0.88	0.87
French	103100	127480	99900	145000	0.87	0.93	0.91	0.95
Danish	10800	56500	148880	193700	0.94	0.94	0.96	0.99
Other Asian	700	2640	38820	238600	1.00	0.80	0.76	0.76
Swiss	43900	84610	112900	116900	0.86	0.96	0.96	0.97
Dutch	25600	50570	89520	128600	0.83	0.90	0.91	0.96
Chinese	33500	206090	79680	55300	0.93	0.78	0.72	0.69
Welsh	37900	76850	92500	73500	0.81	0.85	0.91	0.96
Other European	5400	16230	8040	182600	0.72	0.91	0.86	0.78
Finnish		3000	58880	142800		0.86	0.88	0.90
Greek	300	780	6720	159800	0.67	0.82	0.71	0.84
Portugeuse	3500	18270	35580	110400	0.97	0.56	0.48	0.58
Romanian		150	12480	101300		0.87	0.75	0.86
West Indies	6900	23400	23620	70400	0.74	0.86	0.89	0.95
Belgian	6900	14490	28280	55200	0.78	0.79	0.82	0.88
Spanish	4000	8860	6180	50700	0.98	0.91	0.90	0.85
Turkish		540	7580	20300		0.91	0.73	0.78
South American	1700	6700	3740	16700	0.82	0.84	0.90	0.94
Australian/New Zealander	600	4250	7160	11300	0.67	0.96	0.97	0.95
African	100	3370	2880	5000	1.00	0.57	0.79	0.94
Other	600	2680	460	4100	0.83	0.78	0.91	0.95
Central American		700	680	4600		0.94	0.97	0.96