Main replication results using full-count census data.

	Figure 2 and Table 4. Convergence in occupation score between immigrants and native-born workers by time spent in the US		**Table 5. Age-earnings profile for native- and foreign-born, using alternative income measures**
Main result(s)	In the cross section, new immigrants earn less than natives upon first arrival, but completely make up this gap over time. Controlling for cohort (RCS) reduces the initial earnings gap.	Permanent immigrants in panel data hold slightly higher-paying occupations than natives upon first arrival, and retain this advantage over time.	Initial earnings gap in cross section data is larger when using 1901 earnings, but a large portion of the difference in estimates can be account for by adjusting 1950 occupation-based earnings. The pattern of earnings convergence remains.
I. Alternative method of assigning occupation score			
w / IPUMS occscore[*]	✓	✓	✓
w/ NBER occscore[†]	✓	✓	✓
w/ NBER occscore crosswalk[‡]	✓	✓	✓
LIDO occscore[§]	Pattern holds, but earnings gap with natives persists.	Pattern holds, but all groups have earnings penalty after 30+ years in US	✓
LIDO-style predicted income[**]	Pattern holds, but earnings gap with natives persists.	Pattern holds, but all groups have earnings penalty	✓
II. Alternative ABE/Ferrie matching methods (using NBER occscore crosswalk)			
ABE-NYSIIS: Unique 5-year band	✓	✓	✓
ABE-exact: Unique 5-year band	✓	✓	✓
ABE-exact: Unique 5-year band, exact age	✓	✓	✓
ABE-JW: Unique by exact age	✓	✓	✓
ABE-JW: Unique 5-year band	✓	✓	✓
ABE-JW: Unique 5-year band, exact age	✓	✓	✓
EM: p = 0.70, l = 0.60	✓	✓	✓
EM: p = 0.90, l = 0.75	✓	✓	✓
ML (even weights): b1=0.1, b2=1.3	✓	✓	✓
III. Brigham Young University's Record Linking Lab (BYU) and IPUMS Multigenerational Longitudinal Panel (MLP) matching methods (using NBER occscore crosswalk)			
BYU[††]	✓	✓	✓
MLP[‡‡]	✓	✓	✓

	Figure 3. Earnings gap upon first arrival and after 30 + years in the US, by country of origin	Figure 4. Difference in immigrant penalty for early and late arrival, by country of origin
Main result(s)	Substantial cross-country variation in occupation-based earnings. Permanent immigrants experience relatively little occupational growth relative to natives.	Countries with more recent migration waves (e.g. Russia and Italy) had largest declines in skill level. Old immigrant groups (e.g. English and Irish) had smaller (or no) declines.
I. Alternative method of assigning occupation score		
w / IPUMS occscore	✓	✓
w/ NBER occscore	✓	✓
w/ NBER occscore crosswalk	✓	✓
LIDO occscore	✓	✓
LIDO-style predicted income	✓	✓
II. Alternative ABE/Ferrie matching methods (using NBER occscore crosswalk)		
ABE-NYSIIS: Unique 5-year band	✓	✓
ABE-exact: Unique 5-year band	✓	✓
ABE-exact: Unique 5-year band, exact age	✓	The decline in skill level is similar for countries with older & newer arrival groups.
ABE-JW: Unique by exact age	✓	✓
ABE-JW: Unique 5-year band	✓	✓
ABE-JW: Unique 5-year band, exact age	✓	Some older immigrant groups (including Ireland) experienced large and significant declines in skill level
EM: p = 0.70, l = 0.60	✓	✓
EM: p = 0.90, l = 0.75	✓	✓
ML (even weights): b1=0.1, b2=1.3	✓	✓
III. BYU and MLP matching methods (using NBER occscore crosswalk)		
BYU	✓	Some older immigrant groups (including Ireland and England) experienced significant, albeit relatively small, declines in skill level
MLP	✓	Some older immigrant groups (including Ireland and England) experienced significant, albeit relatively small, declines in skill level

[*] In the original JPE paper, the majority of occupation scores were assigned using a crosswalk between occupation name and occupation score constructed using the 1870-1920 IPUMS census data. In addition, occupations that were not successfully matched to an occupation score were assigned an occupation score by hand when possible. We replicate all the original figures using the original IPUMS occupation crosswalk, without additional hand-coding.

[†] Using the occscore variable included in the full-count censuses for 1910, 1920, and 1930 available through NBER.

[‡] Using a crosswalk that between the variable occ1950 included in the full-count censuses for 1910, 1920, and 1930 and the median occscore for each occ1950 code reported in the NBER data. This allows us to assign occupation information to more of our matched sample.

[§] LIDO scores are assigned to individuals based on their occupation code, age, and state of residence. For a further description see Saavedra and Twinam (2018).

[**] We use the 1940 full-count census to predict income in our linked samples using occupation code, region, age, state of residence, and country of origin.

[††]BYU links were created by researchers at Brigham Young University's (BYU) Record Linking Lab. The crosswalks for 1900-1910 and 1900-1920 are from *Ran Abramitzky, Leah Boustan and Myera Rashid. Census Linking Project: Version 1.0 [dataset]. 2020. https://censuslinkingproject.org*

[‡‡] The 1900-1910 and 1910-1920 Multigenerational Longitudinal Panel (MLP) crosswalks are from *Jonas Helgertz, Steven Ruggles, John Robert Warren, Catherine A. Fitch, Ronald Goeken, J. David Hacker, Matt A. Nelson, Joseph P. Price, Evan Roberts, and Matthew Sobek. IPUMS Multigenerational Longitudinal Panel: Version 1.0 [dataset]. Minneapolis, MN: IPUMS, 2020. https://doi.org/10.18128/D016.V1.0*

Memo on JPE replication results

Summary

Using the newly available full-count census data and the newly available NBER-occupational scores, we have replicated the results from our JPE paper that used a sample of the population and older IPUMS-coded occupational scores. Using the full-count census, our results are similar to, but somewhat more striking than, the original findings. Relative to the original JPE findings, we find that immigrants held even higher paying occupations than the native born upon first arrival[1]. These findings are robust across matching methods, including more conservative versions of the ABE matching approach; more and less conservative versions of the EM algorithm and the Machine Learning (ML) approach; and two different matching methods developed by Brigham Young University's (BYU) Record Linking Lab and the IPUMS Multigenerational Longitudinal Panel (MLP) project respectively. The difference in the results is driven by differences in the way in which NBER and IPUMS coded occupations and not by the larger data or matching methods. The general pattern that immigrants from some sending countries held higher paying occupations and others lower paying occupation remain, but the exact ranking of countries is more sensitive to the dataset used.

Replication steps

In our original paper, we relied on the 1900 IPUMS 5 percent census data to identify men from larger sending countries and used Ancestry.com data to identify men from smaller sending countries. We then linked this data to the 1910 and 1920 census retrieved from Ancestry.com using the standard iterative ABE/Ferrie matching method. Since this paper was published, full-count census data has been made available through the NBER. We first replicated our results with this newly available full-count 1900, 1910, and 1920 census data using the original (ABE) matching algorithm. This full-count census data allows us to increase the sample size of our matched panel data from 65,812 observations to 3,183,414 observations (2,833,191 native-born men and 350,223 foreign-born men) and we find that our results replicate well.

This newly-available census data also allowed us to test the robustness of our results to alternative measures of occupation-based income. In our original paper, the majority of occupation scores were assigned using a crosswalk between occupation name and occupation score constructed using the 1870-1920 IPUMS census data. In addition, occupations that were not successfully matched to an occupation score were assigned an occupation score by hand when possible. We replicate all the original figures using the original IPUMS occupation crosswalk, without additional hand-coding, and find that the hand-coding method only effected a small percentage of observations and does not have any significant impact on the results. Since the assignment of occupational codes is slightly different in the NBER census data, we show our replication results using the full-count census data using both the original occscore crosswalk constructed from IPUMS data, and using the occscore listed in the NBER dataset. Because not all individuals with occupation reported are assigned an occupational score, our preferred method is to use the full-count 1910, 1920, and 1930 NBER census data to create a new crosswalk between occupation name and occupation score. This new crosswalk is constructed in the same way as the original IPUMS crosswalk and the years 1910, 1920, and 1930 are used because they include the

[1] However, this does not hold true when we use the method that builds in an immigrant penalty instead of occupation scores.

necessary variable (occ1950). The original IPUMS crosswalk is able to assign an occupation score to 85.4% of all matches in the full-count census with occupation information, whereas the NBER crosswalk is able to assign occupation score to 93.3% of these matches. We replicate all figures with the full-count census using occupation scores assigned with the IPUMS crosswalk and with the NBER crosswalk. We additionally report our main results using LIDO occupation scores rather than occupation-based earnings. LIDO scores are assigned to individuals based on their occupation code, age, and state of residence. For a further description of the LIDO occupational income measure see Saavedra and Twinam (2018). Finally, we show versions of our main results using "LIDO-style predicted income." In this method, we use the full-count 1940 census to predict the income of men in our matched data set based on occupational code, age, state of residence, and country of birth. Since this method does not perform well for farmers, who often do not report income in the census, we instead assign farmers' income measures based on the method used by Collins and Wanamaker in their 2017 paper.

In addition to the newly available methods of measuring occupation-based earnings, several "second-generation" matching algorithms have been developed. We replicate our results using versions of the ABE algorithm requiring men to be unique by first and last name within a 5-year band, matching on exact name rather than NYSIIS standardized names, and using Jaro-Winkler string distance. We also show results using more and less conservative versions of the EM algorithm, and the Machine Learning (ML) approach.

We further replicate our results using crosswalks created by two different matching methods: BYU's Record Linking Lab method and the IPUMS MLP method. Both these approaches use a combination of hand-linked data and machine-learning algorithms[2].

In our original paper, we only examined heterogeneity by country of origin using 16 European countries (Austria, Belgium, Denmark, England, Finland, France, Germany, Ireland, Italy, Norway, Portugal, Russia, Scotland, Sweden, Switzerland, and Wales) because of inconsistencies in the way in which the variable birthplace was reported for other countries. This resulted in the exclusion of several small sending countries. In our replication, we use the IPUMS classification of birthplaces and include all countries that had more than 3,000 male workers aged 18-35 in 1900. This means that 6 new countries are added to our analysis: Czechoslovakia, Greece, Hungary, Netherlands, Poland, and Romania[3].

Finally, in our original analysis, the data was weighted by place of birth, however, in our replication we have reweighted the matched sample to reflect the distribution of the following variables in the 1920 population: age, occupation category, place of birth, urban status, and literacy. This ensures that our panel samples more closely reflect the actual distribution of these characteristics in the 1920 population. We present the results of our main analysis (shown in Figure 2) weighting only by country of birth. When weighting based only on country of birth, the

[2] For more detailed information on the BYU matching method see Buckles, Kasey et al., "Combining Family History and Machine Learning to Link Historical Records." NBER Working Paper 26227, 2019. For information on the MLP matching method see Fitch, Catherine R et al., "A New Strategy for Linking Historical Censuses: A Case Study for the IPUMS Multigenerational Longitudinal Panel." IPUMS Working Paper 2020-03, 2020.

[3] Note, however, that for some conservative linking methods we do not find any match for some countries. In those cases, the country is added with an empty bar in the figures that analyze heterogeneity by country. Finding no matches for some countries happens because of two main reasons: (i) very small sample sizes (e.g. Portugal), and (ii) inconsistencies in the way in which birthplaces were reported in different census (e.g. Czechoslovakia and Poland in 1910).

occupation-based earnings of the cross section and panel data do not fully converge over time, which suggests that our matched sample is not fully representative of the population.

Key results from our replication exercises:

Figure 2 and Table 4 show the results of our main analysis comparing the occupational mobility of native-born and immigrant workers. We estimate $Occupation\_score_{ijmt} = \gamma_{t-m} + \theta_t + \alpha_j + \beta_1 age_{it} + \beta_2 age_{it}^2 + \beta_3 age_{it}^3 + \beta_4 age_{it}^4 + \epsilon_{ijmt}$, where γ_{t-m} indicates years spent in the US (with native born as the omitted category), θ_t indicates census year (with 1900 as the omitted category), and $\alpha_j$controls for country of origin. The repeated cross section and panel regressions add an indicator for arriving pre- or post-1890 to allow for differences in occupation score by arrival cohort. Note that in the original paper the repeated cross section and panel regressions were run as a pooled regression. This difference explains why the results using the original occupation data and occupation scores shown here (figure 2a) differ slightly from the original JPE results. When using the occupation scores available in the NBER data, we find that immigrants held even higher paying jobs upon first arrival. When the NBER occupation score crosswalk is applied to the full-count data (Table 4d), we find that immigrants earn \$2,074 more than natives upon first arrival, which is a considerably larger gap than the \$450 earnings gap found in our original paper. When using LIDO occscore & our LIDO-style predicted income measure immigrants earn less compared with natives, however this is expected given that both methods assign earnings scores based on state of residence, and we know from the results presented in Table 6 of our original paper that when controlling for state of residence, immigrants experience a greater earnings penalty. While the level of earnings varies, the conclusion that a large portion of the earnings convergence in the cross section is driven by biases due to changes in arrival cohort skill level and negatively selected return migration is robust to all alternative occupation score measures and matching methods.

Table 5 repeats the analysis from Table 4 but using two alternative income measures. In Panel A we show results using occupation-based earnings from the 1901 Cost of Living survey. As in the original paper, we find that immigrants appear to have a much larger initial occupation-based earnings gap with natives when using this measure, but we continue to find that the pattern of convergence in the cross section is largely driven by biases due to changes in arrival cohort skill level and negatively selected return migration. In Panel B of Table 5 we make three adjustments to the 1950 occupation-based earnings score; 1) using only urban workers to calculate the occupation-based earnings, 2) using mean rather than median earnings by occupation, and 3) using the 1900 Census of Agriculture rather than the 1950 Census of Population to infer the earnings of farmers. As in the original paper, we find that these adjustments account for a large portion of the difference in estimates generated by 1950s occupation-based earnings and the 1901 Cost of Living survey.

Figure 3 shows the occupational score gap between native and foreign-born men in the panel sample upon first arrival (0-5 years in the US) and after 30+ years in the US, by country of origin. The original results showed that there was significant heterogeneity in the earnings penalties faced by immigrants from different countries, with immigrants from poorer countries earning less than the native-born upon first arrival and immigrants from wealthier countries earning more than the native-born. Additionally, comparing the earnings gap of immigrants who arrived 0-5 years ago vs. 30+ years ago showed that, as a whole, permanent immigrants experience little occupational growth relative to natives after spending more time in the US. The only countries that showed any significant difference in occupational score gap were Finland and Ireland. When replicating this result using full-count census data, the general pattern of immigrants from poorer countries earning less upon first arrival while immigrants from wealthier countries earning more holds. However, we find that more countries experienced statistically significant convergence in earnings with the native-born population after 30+ years in the US.

Figure 4 reports the difference in earnings penalty of those who arrived in 1880-1884 with those who arrived between 1895 and 1900, by country. We originally found that countries with more recent immigration waves, such as Russia and Italy, had the largest decline in arrival cohort skill level, while older immigrant groups such as English and Irish experienced smaller declines in arrival cohort skill level. When replicating these results on the full-count census with a variety of earnings measures and matching methods, we continue to find that the decline in skill level among immigrants from England & Ireland is less than the decline in skill level among immigrants from Russia and Italy. However, the decline in skill level among English and Irish immigrants is statistically significant in most of our replication specifications.