UPPSALA UNIVERSITET

Uppsala Papers in Economic History (UPEH)

Department of Economic History

Working Paper 2024/12

Did Cities Increase Skills During Industrialization? Evidence from Rural-Urban Migration

Jonatan Andersson & Jakob Molinder

Department of Economic History, Uppsala University; Department of Economic History, Uppsala University and Department of Economic History, Lund University

jonatan.andersson@ekhist.uu.se; jakob.molinder@ekhist.uu.se

Did Cities Increase Skills During Industrialization? Evidence from Rural-Urban Migration

Jonatan Andersson & Jakob Molinder
Department of Economic History, Uppsala University; Department of Economic History, Uppsala University and Department of Economic History, Lund University
jonatan.andersson@ekhist.uu.se; jakob.molinder@ekhist.uu.se

Uppsala Papers in Economic History (UPEH), ISSN 2004-5263
Working Paper 2024/12

DOI: 10.33063/upeh.v3i.578

Date: 5 January 2024

Abstract
The process of industrialization is typically associated with urbanization and a widening urban-rural skills gap. To what extent were these disparities driven by the direct impact on occupational attainment of living in an urban area or the result of the positive self-selection of more-skilled individuals into cities? In this paper, we leverage exceptional Swedish longitudinal data that allow us to estimate the impact of rural-urban migration on skill attainment during Sweden's industrialization from the 1880s to the 1930s using a staggered treatment difference-in-difference estimator. We attribute roughly half of the gap in urban-rural skills to a direct impact of living in an urban area, whereas the other half is driven by self-selection into cities. A third of the direct impact of residing in cities is explained by a static effect, reflecting better initial matching, while the rest is the result of a dynamic effect as individuals upgrade their skills over time in urban areas. We conclude that cities had a substantial effect on skill development in Sweden around the turn of the nineteenth century that is likely to extend to other European and North American economies that were industrializing around the same time.

Keywords: Rural-urban migration, skills, industrialization

JEL: N33, N34, J62, R23

UPEH Uppsala Papers in Economic History

are working papers intended to disseminate research results to other scholars in order to encourage discussion and suggestions before journal publication. The papers have not undergone peer review, but are published at the discretion of the UPEH editors.

UPEH series seeks to be a platform with a broad coverage in terms of timeframe, geographical scope, and methodological approaches. It seeks to disseminate work by economic historians, political economists, business scholars, economists, historians, demographers, geographers, political scientists, sociologists and other social scientists covering a wide variety of topics such as, but not limited to, economic growth, political economy, money and banking, international trade and finance, business, ecology, education, labour markets, inequality, industrial organization, science and technology, consumption, transportation, energy, agriculture, sustainability, health, family/household, advertisement and marketing, institutional economics, history of economic thought and others.

UPEH are usually in English but working papers in any of the Scandinavian languages (Danish, Norwegian and Swedish) are also welcome for publication.

UPEH working papers receive a unique Digital Object Identifier (DOI). The working papers are hosted by the Uppsala University Library (UUB.se) and are available at the homepage of the Department of Economic History, Uppsala University as well as via DiVA, S-WoPEc: Uppsala Papers in Economic History (hhs.se), EconPapers RePEc and IDEAS. A list of UPEH is available at https://journals.uu.se/upeh/issue/archive

UPEH is the continuation of several series that has been issued at the Department of Economic History at Uppsala University since 1983: *Uppsala papers in economic history: Research reports*, ISSN 0281-4560 (1983–2005), *Uppsala papers in economic history: Basic Readings*, ISSN 0282-9142 (1985–1998), *Uppsala papers in economic history: Working papers*, ISSN 1102-1306 (1988–1993), *Working papers in transport and communication history* (1994–1999) and *Uppsala Papers in Economic History*, ISSN 1654-8019 (2007). Uppsala Papers in Economic History are issued in collaboration with the *Uppsala Papers in Business and Financial History* (since 1993). All these printed papers have been digitalised and are thus also possible to download.

Potential working papers should be submitted to the editors: Anders Ögren (anders.ogren@ekhist.uu.se) or Valbona Muzaka (valbona.muzaka@ekhist.uu.se)

Did Cities Increase Skills During Industrialization? Evidence from Rural-Urban Migration

Jonatan Andersson[*] Jakob Molinder[†]

Abstract

The process of industrialization is typically associated with urbanization and a widening urban-rural skills gap. To what extent were these disparities driven by the direct impact on occupational attainment of living in an urban area or the result of the positive self-selection of more-skilled individuals into cities? In this paper, we leverage exceptional Swedish longitudinal data that allow us to estimate the impact of rural-urban migration on skill attainment during Sweden's industrialization from the 1880s to the 1930s using a staggered treatment difference-in-difference estimator. We attribute roughly half of the gap in urban-rural skills to a direct impact of living in an urban area, whereas the other half is driven by self-selection into cities. A third of the direct impact of residing in cities is explained by a static effect, reflecting better initial matching, while the rest is the result of a dynamic effect as individuals upgrade their skills over time in urban areas. We conclude that cities had a substantial effect on skill development in Sweden around the turn of the nineteenth century that is likely to extend to other European and North American economies that were industrializing around the same time.

Keywords: Rural-urban migration, skills, industrialization

JEL: N33, N34, J62, R23

* Corresponding author. Department of Economic History, Uppsala University.
Email: jonatan.andersson@ekhist.uu.se
† Department of Economic History, Uppsala University and Department of Economics History, Lund University.
Email: jakob.molinder@ekhist.uu.se

1. Introduction

Economists and other social scientists have long sought to understand the causes of the urban-rural gap in worker productivity and skills that arise as economies transition from agricultural to non-agrarian activities (Kuznets 1955) and endure long after the transition is complete (Glaeser and Maré 2001). In contemporary developed nations, individuals living in cities demonstrate higher productivity, indicated by the urban-wage premium, and are more skilled. This is defined by either educational level, or the cognitive, motor, or interpersonal skills required by urban occupations (Berry and Glaeser 2005; Bacolod et al. 2009). In developing countries, the urban-rural gap is even more pronounced (Lagakos 2020). Young (2013) argues that spatial disparities in developing countries are entirely driven by the elevated skill intensity in urban production and the sorting of workers between the urban and rural sectors. During industrialization in today's developed nations, historical accounts echoed similar sentiments regarding skill requirements and self-selection into cities (Marshall 1890). Nevertheless, studies in the field of urban economics of contemporary developed economies have underscored the significance of improved learning among workers and better matching between firms and employees as key contributors to the higher productivity and skill levels in cities, alongside positive self-selection (Glaeser 1999; Duranton and Puga 2004). This raises the question of whether the influence of cities on skills is solely discernable in technologically advanced economies with high levels of human capital or whether the effect was also present during the industrialization of today's developed nations. However, this type of analysis is very data intensive. Notably, it requires information that follows individuals over time as they reside in both urban and rural areas, precluding an examination of past societies.

In this article, we contribute to this debate by employing unique longitudinal data from the late nineteenth and early twentieth century, containing detailed information on men and women who lived during Sweden's industrialization. Throughout this period, Sweden experienced a fundamental economic restructuring that coincided with massive, migration-led urban growth, rendering it a compelling historical case for analyzing the impact of urban residence on skills in an industrializing economy. To identify the effects that spending time in urban areas had on skills, we study the skill attainment of rural-urban migrants several years before and after their move. As a proxy for skills, we use occupational incomes, frequently used to study occupational outcomes in historical times when information on individual-level incomes and education is unavailable (see for example Abramitzky et al. 2012). Following de la Roca and Puga (2017), we are interested in disentangling the static and dynamic effects of urban residence on skills from the sorting of high-ability individuals into cities.

We use two complementary datasets. The first is the Historical Swedish Population Panel (HISP), which offers a longitudinal sample of roughly 1,500 individuals with yearly observations from 1880 to 1930. This dataset allows us to pinpoint the timing and dynamics of skill attainment with a high degree of accuracy. The second is a panel of individuals across the four decadal censuses from 1880 to 1910. This dataset allows us to observe individuals only every tenth year, but is much larger than the longitudinal sample and offers information on as many as 900,000 individuals. The large sample size enables us, in this case, to examine specific dimensions in greater detail, as the data can be broken down into subgroups without compromising statistical precision.

The fact that we can observe the same individual over several years or census waves provides us with two advantages. First, it allows us to investigate whether the impact of relocating from a rural to an urban area on skills is a one-off effect, or if it accumulates over time as the individual spends more time in an urban environment. Second, we can employ individual-fixed effects to assess any differences in trends between migrants and non-migrants before the migration event. We do this by implementing a staggered treatment difference-in-difference regression design.

Our findings reveal a substantial effect of living in an urban area on skill attainment during industrialization. First, we observe a static effect of migration on occupational upgrading. Rural-urban migrants did not exhibit differing trends in skill attainment relative to non-migrants before their relocation but, immediately upon settling in the city, they experienced a 5 percent increase in occupational income compared to the counterfactual scenario of remaining in the rural area. Second, we identify a dynamic effect of transitioning from a rural to an urban area. Over time, migrants acquired more skills compared to what they would have accomplished in the countryside. After spending 20 years in urban environments, they had about 10 to 15 percent higher occupational incomes than if they had not moved.

The long-run effect of 10 to 15 percent can be compared to the cross-sectional occupational income advantage, which was stable at about 30 percent throughout the period. This implies that we can attribute about half of the cross-sectional difference to the direct effect of cities on individuals, while the remaining half was due to more-skilled individuals sorting into urban areas. Furthermore, while a third of the long-run effect of cities on skills is accounted for by the immediate upgrading in occupational status when relocating to an urban area, the remaining two-thirds is explained by the dynamic nature of urban economies. Over time, individuals moving to urban areas successfully moved up the occupational ladder faster than those who remained in rural areas.

We are also interested in the relationship between agglomeration size and skill attainment—often referred to as scaling relationships—to determine whether our results are influenced by city size.[1] We divide our census dataset into two parts: one comprising Sweden's capital and largest city, Stockholm, and the other encompassing all other cities. Even though Stockholm was the sole city with a population exceeding 500,000 at any point during the studied period, we do not observe any additional gains from moving to Stockholm in comparison to other cities. Consequently, we must infer that the effect of cities on skill attainment during industrialization was not driven by agglomeration size but, rather, by the unique characteristics of the urban labor market. We believe that this observation makes our results generalizable to other Western European and North American industrializing economies, as cities in the industrialization era were quite often similar in size to Stockholm.

Moreover, we explore the extent that cities effectively facilitated occupational upgrading for individuals who initially possessed relatively low skills before entering the urban economy. In the context of industrializing economies, a significant proportion of the population had limited skills and was primarily engaged in the agricultural sector. To ascertain whether cities successfully enhanced the skills of the unskilled, we divide our linked census dataset into two categories: individuals whose occupational incomes before relocating to a city were higher than the overall median occupational income; and individuals with lower than median occupational income before the move. Our analysis reveals that living in a city had a more pronounced effect on skill attainment for those who were relatively unskilled before moving compared to those who were relatively more skilled. This finding leads us to conclude that cities played a fundamental role in increasing the skill attainment of the least skilled during industrialization.

Our article contributes to three bodies of literature. Specifically, our study addresses the debate on learning and matching in cities. Theory suggests that in urban areas, the larger pool of workers and firms should allow for more effective matches between employers and employees, as well as leveraging continuous learning among workers (Glaeser 1999; Duranton

---

[1] Scaling relationships of various strength are often found in studies of contemporary societies (see for example Bacolod et al. 2009; Baum-Snow and Pavan 2012; Keuschnigg et al. 2019)

and Puga 2004; Yankow 2006; Bacolod et al. 2008; de la Roca and Puga 2017). We extend the test of this theory by examining urban skill acquisition in an industrializing economy during the late nineteenth and early twentieth centuries. This was a period when technology and human capital were considerably less developed than today and the workforce was transitioning from primarily agricultural activities.

Second, we contribute to the debate in economic history on the effect of internal migration on labor market outcomes during industrialization. As the industrialization process unfolded in Europe and North America in the nineteenth and early twentieth centuries, new work opportunities emerged in cities and industrial towns. There is a rich literature dealing with the effects on social mobility and economic returns of moving to such places (Long 2005; Collins and Wanamaker 2014; Eriksson 2015; Ward 2021). This literature has relied on cross-sectional or, at best, brother-fixed effects to study the economic outcomes associated with migration. This paper advances this literature in two ways. First, we offer a novel perspective on the way that cities affected the skill attainment of urban migrants. Second, we provide longitudinal data that allow us to account for pre-existing trends and provide a more robust analysis. Thus, we are the first to study the long-term effects of living in a city on skill attainment during industrialization.

Third, we contribute to the literature on urbanization and economic growth during industrialization. Seminal works by Kuznets (1968), Bairoch (1988), and Allen (2009) underscore the pivotal role of cities in enhancing efficiency and worker productivity, thereby fostering long-term economic development during the industrialization phase. In addition, the existence of urban wage premiums during the transition from agriculture to industry is well-documented for several countries (Williamson 1988; Hatton and Williamson 1993; Prado and Lundh 2015; Boustan et al. 2018). However, the underlying reasons for this urban productivity advantage have remained relatively unexplored. It is unclear whether the boosted productivity of urban individuals simply reflects the sorting of workers or if it is derived from working and living in an urban environment, as was already suggested by Marshall (1890). Our study adds to this literature in two crucial ways. First, we leverage unique historical longitudinal data to examine the dynamic effects on skill attainment from living in a city during industrialization. Second, we use a state-of-the-art staggered treatment difference-in-difference technique to allow for a causal interpretation of our results.

The rest of the article is organized as follows. First, we introduce the concept of learning in cities and its application in greater detail. Second, we provide a brief description of the historical context of urbanization and industrialization in Sweden from the middle of the nineteenth century to the interwar period. Third, we present the two datasets used in our analysis, along with our occupational income measure. Fourth, we describe our empirical strategy. In the fifth section, we present and discuss our results and run a series of robustness tests. The sixth and final section gives conclusions.

2. Drivers of skill attainment in cities

Cities were crucial in fostering economic growth during industrialization. Adam Smith (1776) claimed that the commerce and manufacturing activity of cities were the cause—not the effect—of economic growth. In terms of the urban labor force, in the late nineteenth century Alfred Marshall (1890) already suggested that workers in urban environments benefitted from working in a dense environment because of the learning and spillover effects from other workers. Later works by Jacobs (1969) and Lucas (1988) emphasize the role of cities in fostering productivity and economic growth through group interactions. Building on these ideas, Glaeser (1999) develops a model focusing more on rapid human capital accumulation in cities as a result of urban people learning faster through the imitation of more-skilled individuals. Individuals become more skilled through random contact with skilled people. In urban areas the number of human interactions is higher and, thus, increases the pace of learning.

During industrialization, when educational attainment through formal schooling was limited, there is reason to believe that learning through the imitation of more-skilled co-workers was even more important than today. In apprenticeships, a common way of entering a skilled occupation at the time, imitating more-skilled workers was naturally a central feature. However, the majority of urban residents did not have the fortune of entering such a position. Instead, they must have been confined to 'learning-by-doing' and copying more-skilled workers in the workplace.

Although the share of skilled individuals in cities is greater than in the countryside, something also true during industrialization, to what extent can this be attributed to the effect of living in an urban environment? Indeed, there is reason to suspect that high-skilled workers may be disproportionately attracted to the amenities in cities. The gap in skills between cities and the countryside might, therefore, solely reflect positive self-selection on skills into cities. Moreover, if cities do influence the skills of individuals who are living there, how much of this effect can be attributed to better immediate matching of individuals to more skilled occupations, and how much can be attributed to the process of skill attainment over time?

Recently, trying to understand the productive advantage of big cities, de la Roca and Puga (2017) have developed a model to explain the reasons for higher earnings in cities. They consider three reasons that tie into the debate on the urban-rural gap: spatial sorting, static advantages from living in a city, and learning by working in a city. First, more productive individuals may choose to move to cities due to the reasons explained above. Second, there may be a static effect of production in cities that raises the earning of urban workers, as in agglomeration economics. Third, there is a Glaeser-like dynamic effect, in which cities have an advantage in facilitating experimentation and learning, that increases the productivity and earnings of urban individuals over time.

3. Cities and migration during Sweden's industrialization: A brief overview

For much of the nineteenth century, Sweden was one of the least urbanized countries in Western Europe (Bairoch and Goertz 1986). In 1820, only one out of every ten individuals resided in an urban area. Moreover, most of Sweden's cities were small-market towns with less than 2,000 inhabitants. However, a significant shift in urbanization began in the mid-nineteenth century. In 1880, the first year of our study period, urbanization rates had only started to show a recent upward trend, with approximately 15 percent of the population living in urban areas. Over the following decades, Sweden's urbanization would undergo a remarkable transition. The urban population share in Sweden increased by 3.7 percentage points, on average, per decade. As a result, in 1940 nearly 40 percent of Sweden's population resided in towns (Nilsson 1992).

As in other European countries, the process of increasing urbanization rates was parallel to changes in the economic structure. Sweden, in the mid-nineteenth century, was essentially an agrarian country where three out of four individuals were employed in agriculture. However, the agricultural sector underwent several improvements during the first half of the nineteenth century. Increased demand for agricultural products and institutional change raised the earnings of farmers. This, in turn, stimulated domestic demand for consumer goods during early industrialization. Yet, the real industrial breakthrough did not take place until the 1860s with the expansion of the sawmill industry in northern Sweden and investments in the iron-industry and railroad system (Schön 2000).

A significant portion of the initial industrialization process was focused on export-oriented industries in forestry and iron products and was primarily situated in the countryside, which was common before the arrival of improved transportation technology (see, for example, Atack et al. 2022 for insights into the experience of U.S. manufacturing). However, a noticeable shift in economic activity towards cities began in the 1880s, coinciding with the start of our study, and continued through the early 1900s. This period was characterized by rapid urban growth. Notably, the fifteen fastest-growing cities contributed to half of Sweden's population growth. This urban expansion occurred simultaneously with the growth of both the manufacturing and the service sectors at the expense of agriculture. Furthermore, while the key sectors of industrial expansion—namely sawmills and iron production—stagnated, there was significant growth observed in manufacturing industries focused on shoes, textiles, cement, and pulp. However, the majority of Sweden's population still worked in farming as late as the 1920s (Schön 2000). 'Farmer' was a very common career for countryside men throughout our study period so, in a robustness test, we show that our results are not solely driven by disparities in skill attainment between farmers and non-farmers; to be specific, we expect farmers to have been considerably less likely to change occupations when compared to others.

The emerging industries and growing demand for services presented new employment prospects within cities, drawing residents from the countryside. During the late nineteenth century, industrial towns absorbed half of the total urban migration influx. However, over time, Stockholm's attractiveness increased substantially. By the 1930s, migration to Stockholm alone constituted two-thirds of the total urban migration gains (Swaine Thomas 1941). Despite the dominance of Stockholm as a destination for the rural-born, it appears that relocating to the city did not offer any particular advantage for skill attainment relative to other cities. Norman (1974) argues that internal migrants in the early twentieth century who headed for Stockholm did not experience better labor market outcomes compared to those migrating to other Swedish towns. We can confirm this finding in our study using modern econometric techniques.

4. Data

4.1 Individual-level datasets

We use two complementary sets of data that build on the same original source material. The first is the HISP longitudinal sample of men and women born in 1860, 1870, 1880, 1890, and

1900, derived from catechetical examination registers. Each individual is followed over time. The second is taken from linked populations censuses, taking cross-sectional excerpts from the catechetical registers in 1880, 1890, 1900, and 1910. The two datasets complement each other in that they originate from the same source material but have different properties.

On the one hand, the longitudinal HISP sample includes a smaller number of individuals (1,431) but has a high number of yearly observations per individual (28 on average). On the other hand, the linked decadal censuses include a much larger number of individuals (894,702), but a small number of observations per individual (4). Thus, the yearly observations in HISP allow us to identify more precisely the dynamics of the impact of rural-urban migration on occupational income. Since it allows us to observe migrants in the years just prior to the migration event, we can address any suspicion that there are pre-event trends in the trajectory of occupational income, as well as to examine the immediate impact of rural-urban migration on occupational income. Additionally, HISP covers a longer time span, covering the period from the 1870s to the 1930s. The census data, by contrast, allow us to examine the varying impact related to the type of destination and the characteristics of the mover, such as gender and pre-migration skill level.

The HISP dataset covers all migrations made by the randomly sampled individuals from birth until death, emigration, or censoring in the 1930s, which is the end of the period of interest. This allows us to observe all migrations that were made, in addition to information on occupation and demographical characteristics such as marital status, number of children, and socio-economic background, during the entire period before and after the rural-to-urban move occurred. The sample is representative in terms of rural and urban status, socio-economic background, geography, and gender. The data build on catechetical examination registers and parish books in which whole households have been reconstructed for many periods. The original source is well known for its high quality (Dribe and Quaranta 2020). The registers were kept by the local clergy, which documented parish members along with their occupations and, if they moved, migration destinations. These sources are, thus, deemed highly accurate even when dealing with a geographically mobile population.

The population censuses for 1880, 1890, 1900, and 1910 are provided by IPUMS (2020) and have been linked by Eriksson (2015) and include almost the same variables as the longitudinal sample. Although the censuses do not provide information on the exact timing of rural-urban moves, they cover a larger portion of the population and, accordingly, allow us to break down the data into smaller groups. Since the timing of migration is unknown, we are only able to say for certain that an individual migrated between two censuses: ten years apart. Nevertheless, we believe that the combination of the HISP data and the population census gives us a unique ability to explore both longitudinal dynamics, as well as variation across different groups.

Both the census and HISP datasets were originally constructed using information excerpted from catechetical registers and are therefore comparable. Moreover, linking rates of historical records in Sweden have proven to be higher than those typically achieved for other countries.[2] Like all historical sources, our datasets do have some drawbacks, however. Most importantly, there may be concerns that the catechetical registers underreported occupations of adult sons and daughters living in the households of their parents. To assess whether our results are merely a consequence of underreporting, we conduct a robustness test in which we impute the occupational incomes of adult sons and daughters who lack occupational titles. For adult sons, we impute the occupational income of farmhands. For adult daughters, we impute the occupational income of domestic servants. This corresponds to the type of work that the sons and daughters of farmers were engaged in on the family farm.

4.2 Income scores

To assess the skill levels of occupations, we match occupations with occupational income scores, representing the median income associated with each occupation. Using income scores to study labor market outcomes and occupational mobility has become the standard approach in the economic history literature for economic outcomes when information on incomes is not accessible (see, for example, Abramitzky et al. 2012). Our occupational income scores for Swedish occupations have been obtained from Berger et al. (2023), based on tax records for 1900 collected by Bengtsson et al (2021). In Appendix Figure A3, we show that the occupational income scores that are used correlate well with the widely used HISCLASS ordinal occupational scheme, measuring workers skills. Thus, we are confident that the occupational income scores dataset is a suitable proxy for skills.

Our coding procedure follows a two-step process. First, all occupations in the datasets have been assigned five-digit HISCO codes (Leeuwen et al. 2002). Second, we match

[2] Berger et al. (2023) shows that linkage rates between two Swedish censuses 30 year apart (1880-1910) is 57.1 percent. Linking rates for other countries during the same period, range from 20.3 percent for Britain and 21.9 percent for the U.S. to 37 percent for Norway.

the HISCO coded occupations with occupational income scores for each individual-year observation where information on occupation is available. The occupational income scores reflect only cross-sectional snapshots of incomes of occupations at a single point in time. The income scores do not capture changes in incomes over time, a limitation of our study that is shared by most historical studies employing individual-level data. However, we address this limitation by conducting a robustness test using an alternative occupational income score for 1930.

4.3 Descriptive statistics

Table 1 and Table 2 summarize the log-mean occupational income of individuals by urban-rural residency and gender. The first table presents the descriptive statistics of the longitudinal HISP sample and the second table presents the descriptive statistics of the linked censuses. Mean occupational incomes are highly similar between the two datasets despite their different properties. This is also noticeable when looking at the most frequently observed occupational titles that are exactly the same in the two datasets. Rural men were predominately farmers, while urban men were predominately laborers. For urban and rural women alike, domestic servant was the most common occupation.

Table 1. Log income scores by gender and rural-urban residency in longitudinal sample

		Mean (1 + ln occupational income)	Most frequent occupational title
Rural	All	6.35 (0.86)	
	Men	6.63 (0.31)	Land-owning farmer [*Hemmansägare*]
	Women	5.45 (1.33)	Domestic or farm servant [*Piga*]
Urban	All	6.53 (1.1)	
	Men	6.92 (0.58)	Laborer [*Arbetare*]
	Women	5.78 (1.42)	Domestic servant [*Piga*]

Source: For a presentation of HISP, see (Andersson 2023).
Note: Standard deviations within parentheses

Table 2. Log income scores by gender and rural-urban residency in linked censuses

		Mean (1 + ln occupational income)	Most frequent occupational title
Rural	All	6.43 (0.72)	
	Men	6.61 (0.31)	Land-owning farmer [*Hemmansägare*]
	Women	5.43 (1.29)	Domestic or farm servant [*Piga]*
Urban	All	6.46 (1.11)	
	Men	6.88 (0.56)	Laborer [*Arbetare*]
	Women	5.41 (1.41)	Domestic servant [*Piga*]

Source: IPUMS (2020)
Note: Standard deviations within parentheses

Table 3 presents the summary statistics of migration and urban-rural residency from the same samples. Geographical mobility was very high: 24 percent of the whole longitudinal sample, at some point, migrated to an urban area. This is similar in developing nations today, where 20–25 percent of rural residents migrate to urban areas (Young 2013).

The linked census data show a somewhat similar pattern in rural-urban and urban-rural migration, although the migration rates are much lower than in the longitudinal sample. About 9 percent of the individuals in the linked census, at some time, moved to an urban area. We attribute the disparities between the linked census and panel datasets in migrant rates to three underlying factors: the censuses not capturing all transient moves, the extended time coverage of the longitudinal sample compared to the linked census data, and the longitudinal sample having a broader coverage of the life course.

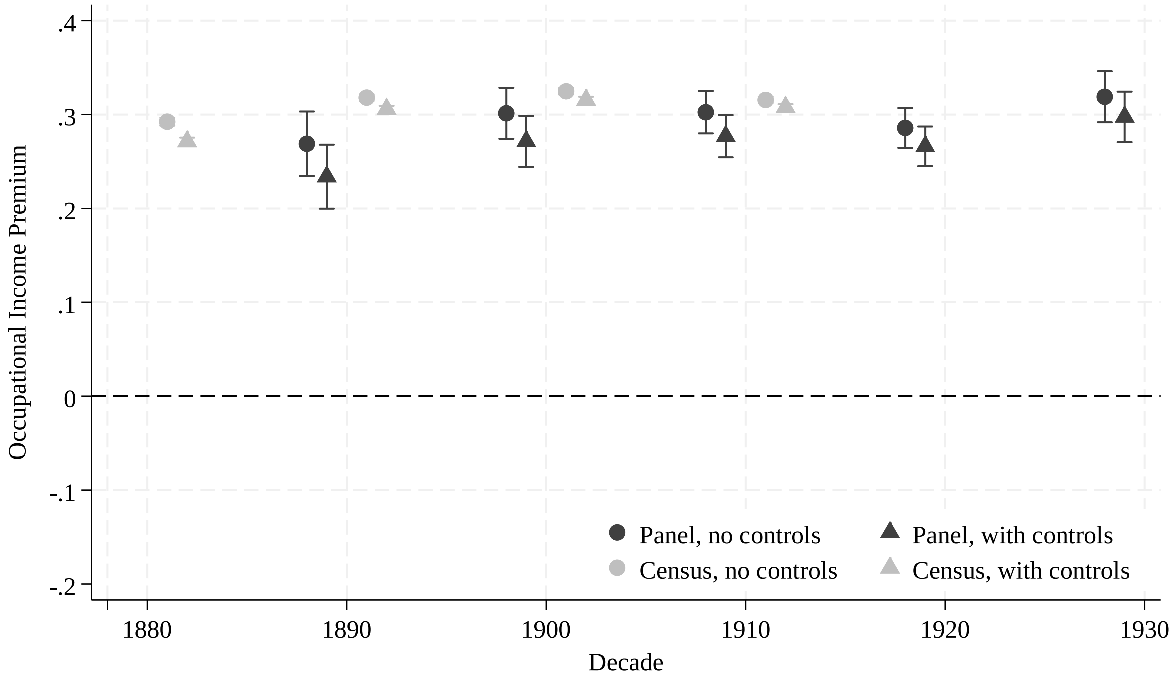
Table 3. Urban-rural status and migrations in longitudinal sample and linked census

	Number of individuals	Number of individuals
	Longitudinal sample	Linked censuses
Urban born	597	170,510
Rural born	1273	724,192
Rural-urban migrants	354	79,867
Share migrants	25%	9%

Source: Andersson (2023); IPUMS (2020)

Figure 1 presents the cross-sectional difference in average occupational incomes between cities and the countryside, referred to here as the urban-rural skills gap. We use observations from both of our datasets and can conclude that the skill disparities are highly similar across time and between the datasets. There is a consistent difference of about 30 percent in skills or occupational income. This is also true after controlling for demographic characteristics, gender, and age.

Figure 1: Cross-sectional Urban Occupational Income Premium



Source: Andersson (2023) and IPUMS (2020)
Note: Demographic controls include a polynomial for age, and dummy variables for sex, number of children, and marital status.

5. Empirical strategy

The longitudinal properties of our datasets, in combination with a clearly specified event, provide an ideal setup for a difference-in-difference design. We exploit the fact that we can track the same individuals for several years both before and after their migration to an urban area. Simultaneously, we have a control group of non-migrants who are subject to the same duration of observation at our disposal. This allows us to observe individual-level occupational incomes among both migrants and non-migrants consistently over extended periods. If the trends in the occupational income of migrants and non-migrants were parallel before the event, it provides us with a unique opportunity to interpret causally the effect of rural-urban migration on skill attainment within the context of an industrializing economy in the nineteenth century.

In our baseline specification, we estimate the following model:

$$ln\ Occupational\ income_{it} = \gamma_i + \lambda_t + \delta Migrant_{it} + X_i + \epsilon_{it}$$

Where $ln\ Occuptional\ income_{it}$ is 1 + the natural log of the occupational income, which we use as a proxy for skills, of individual i at time t. $\delta Migrant_{it}$ equals 1 for rural-urban migrant i for the years t after the move took place; γ_i denotes individual fixed effects, capturing unobservable time-invariant individual-specific characteristics; and year fixed effects, λ_t, captures unobservable time-varying effects on occupational income. Finally, X_i is a vector that comprises individual-level control variables.

We recognize that the canonical difference-in-difference design—with two groups and two time periods—produces unreliable results when applied to settings with multiple units and periods, usually referred to as the two-way fixed-effects (TWFE) estimator with leads and lags. The TWFE estimator can exhibit bias when treatment occurs over multiple years and treatment effects are heterogeneous over time, an issue that recently received much attention (see for example Callaway and Sant'Anna 2020; de Chaisemartin and d'Haultfoeuille 2023; Sun and Abraham 2021). In such cases, the estimator essentially equals "a weighted average of all possible two-group/two-period DD estimators in the data" (Goodman-Bacon 2019). Moreover, Goodman-Bacon (2019) notes that the weighted average is proportional to group size and variance of the treatment dummy, and is highest for groups treated in the middle of the panel. The most consequential implication of this is that if the treatment effect is heterogeneous across time then already treated units become controls and, as a result, negative weights can emerge.

The characteristics of a panel with multiple treatment periods are evident in both of our datasets. In the longitudinal sample, treatment can occur at any point during the period, whereas in the linked census data the treatment can take place in between the four snapshot censuses. Moreover, based on the observations by Glaeser and Maré (2001) on the wage growth effect of living in a city, we suspect that the effect of moving to an urban area on skill attainment varied over time. Consequently, if we were to use the canonical TWFE difference-in-difference methodology, our estimates would likely be biased. To address this issue, we employ the de

Chaisemartin and d'Haultfoeuille (2023) estimator, applied to panels with multiple treatment periods and robust to the presence of heterogeneous treatment effects.

The de Chaisemartin and d'Haultfoeuille (2023) estimator has recently been utilized in several works (see for example Andersen 2020; Braghieri et al. 2022). However, there are several alternative estimators that handle dynamic difference-in-difference designs, such as those devised by Callaway and Sant'Anna (2020) and Borusyak, Jaravel, and Spies (2021). In Appendix Figures A1 and A2, we show that the results are robust to using these alternative estimators.

In the difference-in-difference framework, a key assumption is parallel trends of the treated and untreated group prior to the event. Having access to longitudinal panel data with multiple yearly observations before the event, we can ensure that the parallel-trends assumption holds for a ten-year window in the case of the panel data, and for two census waves in the case of the census data.

We also include several time-variant control variables in our regressions that could influence skill attainment in our regressions, such as living in the parental home, age, age squared, and number of children. We run our models both with and without controls and find estimates of similar magnitude.

6. Results

6.1 Baseline results

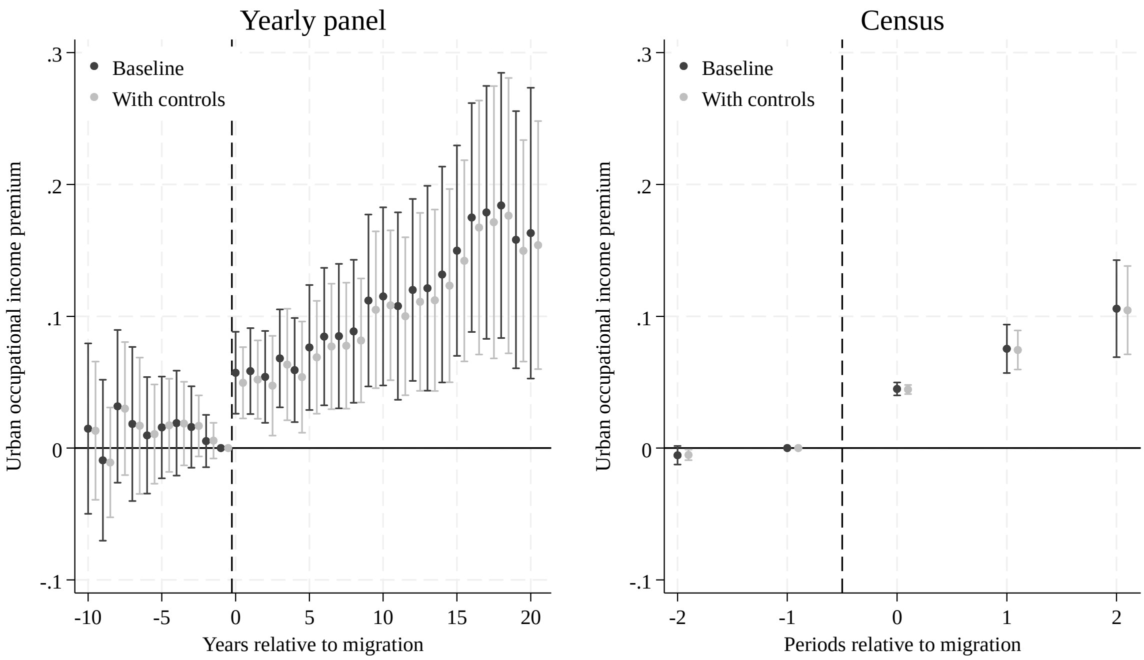
We begin our analysis by examining the impact on occupational income of movers in both datasets to study the effect of urban residence on skills. For the longitudinal HISP sample, the left panel of Figure 2 shows the estimates by plotting the differences in occupational income of migrants and non-migrants up to ten years prior to the move, the year the move took place, and up until 20 years after the move. For the linked censuses, we plot the same estimates but for two census waves (decades) prior to the move up until three periods after the move took place. This is shown in the right panel in the Figure 2. The corresponding coefficients are presented in appendix Table B1.

The results show that individuals gained substantially from relocating to an urban area. Conditional on individual- and time-fixed effects, occupational income did not differ between migrants and non-migrants prior to relocating and, accordingly, migrants do not seem to have experienced different pre-event trends in occupational income. However, the occupational income of migrants increased immediately after arriving in cities and continued to grow over time. Occupational income increased by about 5 percent directly upon arrival, increased to about 10 percent after ten years and further to about 15 percent twenty years after moving.

The size of the estimates using the linked census data is similar to the results from the longitudinal data, although slightly smaller. The trends over time are very similar, however. Migrants increased their occupational income by 5 percent when entering the urban environment and improved upon their occupational income over time. The difference in the results is likely due to the better coverage of the individuals in the longitudinal sample.

Controlling for potential confounders does not alter the results. In Figure 2, the results that include controls for demographic characteristics are not markedly different from the baseline specification without controls.

Figure 2: Effect of rural-urban migration on occupational income

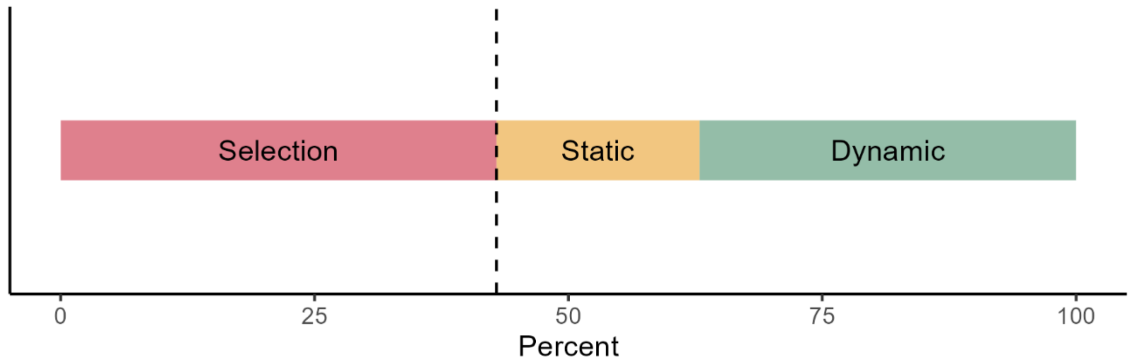


Source: Andersson (2023) and IPUMS (2020).
Note: Controls include a polynomial for age, and dummy variables for sex, number of children, and marital status.

The absence of pre-event trends in occupational income prior to the move, accompanied by a large effect right after the migration event, suggests that relocating to an urban area had a causal impact on skill attainment. Moreover, the results from our regressions suggest the existence of a dynamic growth effect: a substantial portion of the skills of rural-urban migrants accumulates over the time spent in urban areas.

Figure 3 shows the components that produce the urban-rural skills gap. The effect of living in a city explains about half of the urban-rural disparities in skills. First, we identify a static impact of living in an urban area. This effect is the immediate benefit of entering the urban labor market, which must be explained by the advantages of the relatively more-skilled urban sector. The other benefit of living in a city is the dynamic effects on skills. As individuals spend time in cities, they match with better and more skilled occupations. Consequently, individuals in cities initially increase their occupational income by 5 percent. However, after twenty years in the urban environment, their occupational income grows to 10 to 15 percent relative to what it would have been if they had remained in a rural area. The remaining difference in the 30 percent urban-rural skills gap is attributed to unobservable heterogeneity in ability, captured by the individual fixed effects.

Figure 3: Components disclosing the urban-rural skills gap



6.2 Heterogeneity

Drawing on insights from research on agglomeration economies regarding the relationship between city size and productivity (Duranton and Puga 2004), as well as findings from the economic history literature concerning the greater economic gains from migration for those with the most economically disadvantaged backgrounds (Ward 2022), we now move on to explore heterogeneity in treatment effects based on city characteristics and the skill level of individuals prior to relocating to a city. We also consider potential differences between men and women in the impact on skill formation due to spending time in urban areas.

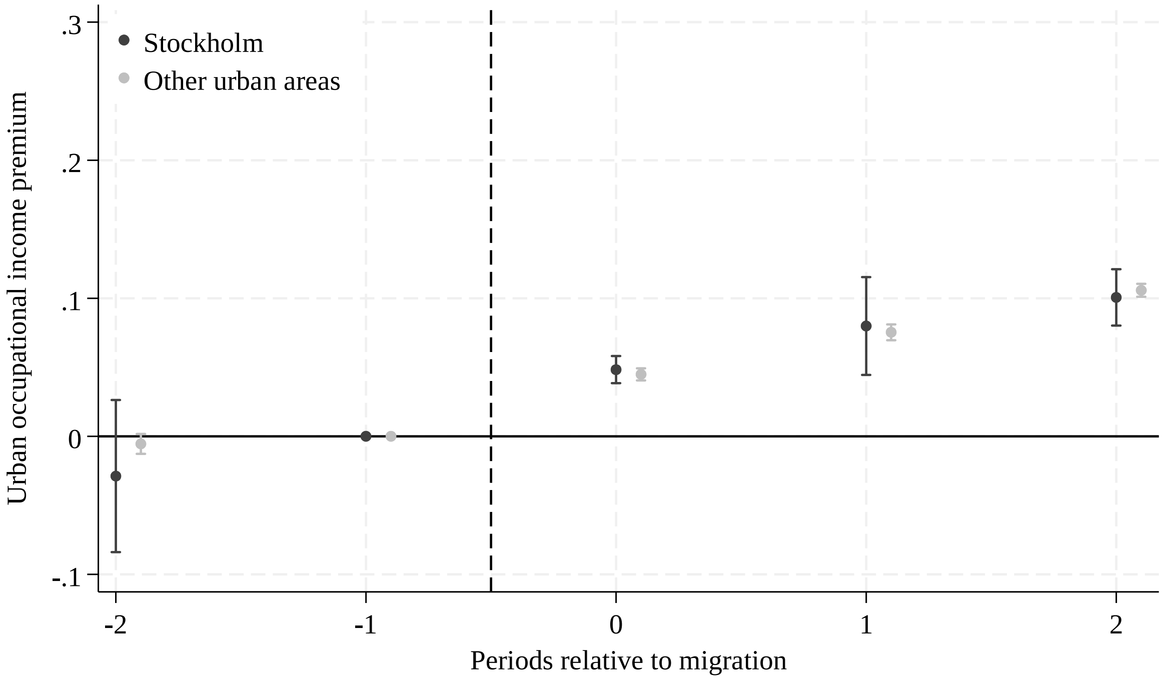
Agglomeration size

To what extent did skill attainment vary by city size? A large amount of literature, spanning both developing and developed economies, indicates that the effect of migration on income tends to be more substantial for those moving to densely populated and larger agglomerations (for a comprehensive discussion, see Henderson et al. 2001). In the context of industrializing Sweden, we investigate this proposition by examining Stockholm separately from other towns. As previously mentioned, Stockholm was the sole Swedish city that attained a population of more than 500,000 during the period. Stockholm, like other larger capitals such as London and Paris, also attracted rural-urban migrants hailing from across the country. Moreover, it was home to numerous large high-technological manufacturers that were at the forefront of the second industrial revolution, as well as the center for relatively human-capital intensive services such as banking, government agencies, and creative industries (William-Olsson 1984).[3]

In Figure 4, we present the outcomes depicting the effect of relocating from the countryside to Stockholm in comparison to moving from the countryside to any other city across Sweden, using the same difference-in-difference design as earlier. As in our previous analysis, we find that migrants had similar levels of occupational income as non-migrants prior to relocating. Upon moving to a city, migrants experienced a substantial increase in their occupational income, which continued to grow over time. However, we find no significant disparities in the effect on occupational income from moving to Stockholm than any other city.

[3] Examples of manufacturing firms that were active in the city are the Ericsson Phone Company and AB Atlas (today Atlas Copco).

Figure 4*:* The effect of urban residence on occupational income in Stockholm and other urban areas



Source: IPUMS (2020).

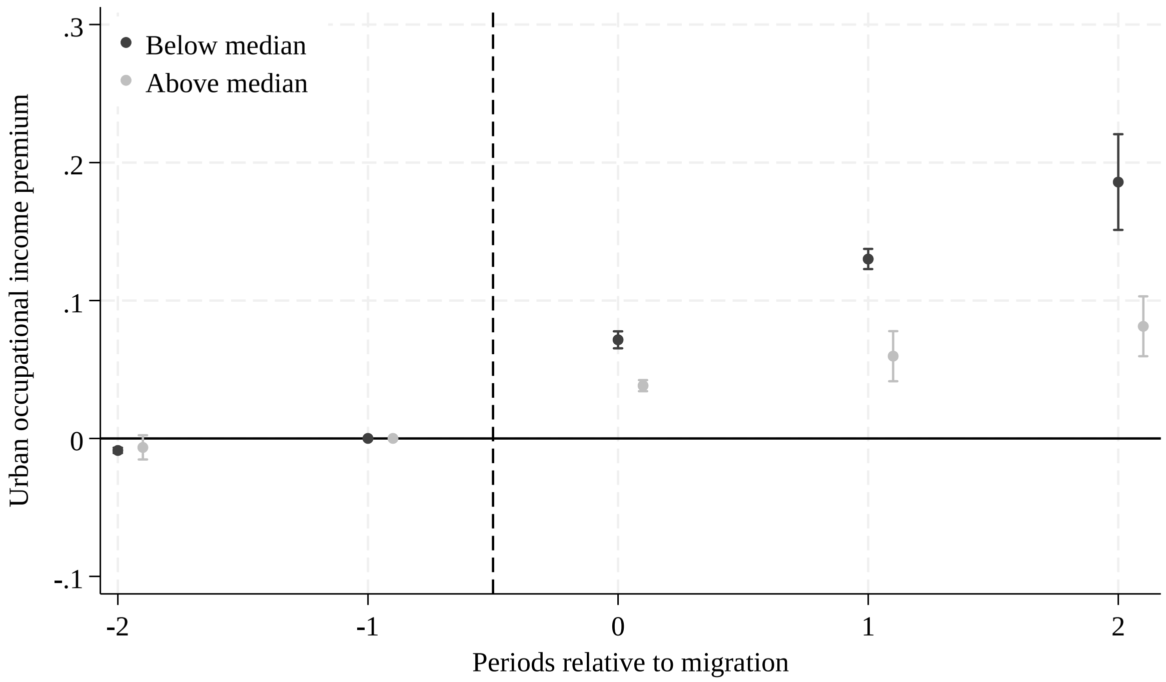
The fact that we find similar returns on migration for individuals who moved to Stockholm compared to those who moved to other, smaller urban areas has implications for the external validity of our results. The urban areas that individuals moved to in the United States or the United Kingdom are more likely to share similarities in size with Stockholm than other Swedish towns. The similar returns thus suggest that our estimates for rural migrants to Stockholm are likely also to be applicable to industrializing countries with larger cities. Consequently, we observe an effect on skills from living in dense areas with more diverse economies rather than a scaling relationship in which skills increase by agglomeration size.

Pre-migration skills

We now move on to examining treatment effects that vary based on pre-relocation levels of skill. We are especially interested in assessing the impact of relocating to an urban environment on skill attainment for individuals who possessed relatively limited skills prior to leaving a rural area. From history, we know that the more human capital-intensive industries of the second industrial revolution increased the demand for skilled workers, while a large share of people at the time were still employed in the agricultural sector as unskilled laborers. This area of investigation is compelling due to the potential of cities to transform those individuals who possessed the lowest levels of skills into skilled workers.

To explore this, we classify individuals into two groups: the ‘skilled group’, consisting of those with occupational incomes exceeding the median prior to the move; and the ‘unskilled group’, comprising those with occupational incomes below the median before their relocation. Our regression reveals significant differences in effects from relocating to an urban area between these two groups. While both groups gained from relocating to a city, those who initially had lower levels of skills stood to gain considerably more, in relative terms, from moving than those with higher levels of skills. The long-run gain for the lower-skilled group was around 20 percent, while the corresponding figure for the higher-skilled group was about 8 percent. Moreover, we observe a striking skill-development pattern among the lower-skilled group, whereas the occupational income of the more-skilled group grew more slowly over time. Hence, cities played a particularly vital role in enhancing the skills of individuals who began with relatively limited human capital.

Figure 5*:* The effect of rural-urban migration on occupational income by pre-treatment occupational income level

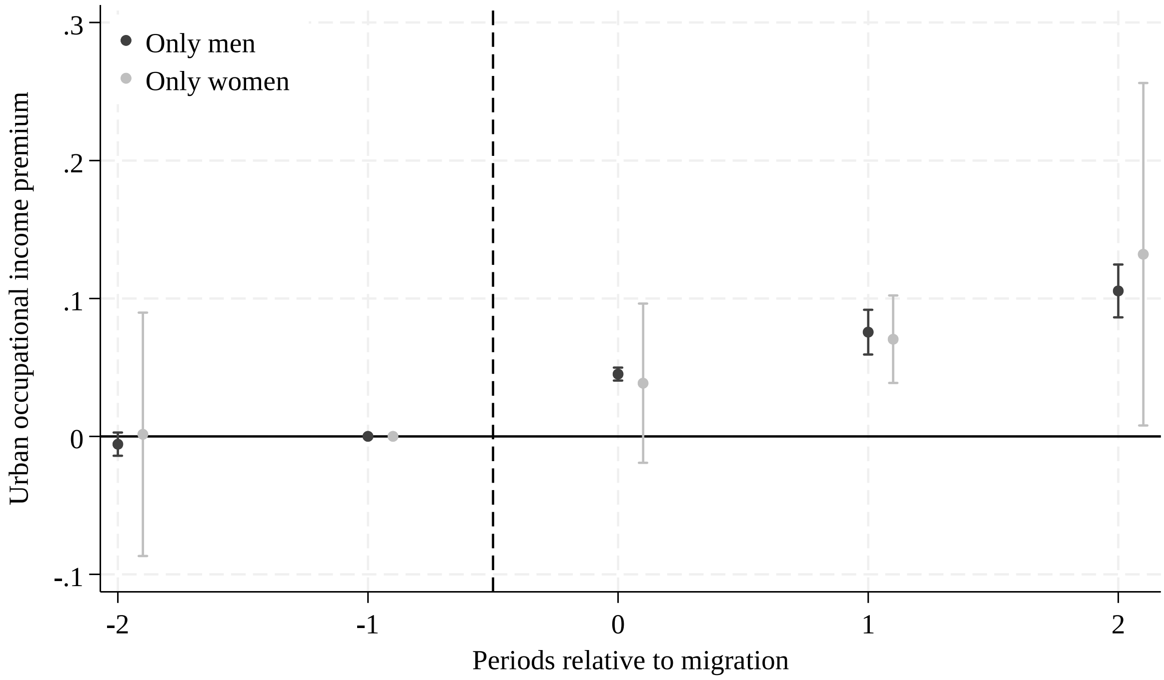


Source: IPUMS (2020).

Differences by gender

There might also be concerns regarding differences in treatment effects by gender. During the industrialization era, women faced legal barriers that prevented them from entering certain occupations and had, in practice, fewer options in the labor market when compared to men. Does the positive effect of cities on skills solely apply to men? To answer this question, we divide our data by gender. Given that the smaller number of individuals in the panel dataset means we have a limited number of observations of female occupational incomes, we exclusively utilize the linked census data in this analysis. The results, presented in Figure 5, indicate that men and women actually seem to have benefited equally in terms of skill development from living in cities. While the estimate is less precise for women than for men, the size of the long-run effect is very similar for both genders.

Figure 6: The effect of rural-urban migration on occupational income for men and women



Source: IPUMS (2020).

7. Robustness

In this section we perform a series of sensitivity tests to probe the robustness of our results. We start by considering the impact of using an alternative measure of occupational income and then move on to test whether the results are robust to the exclusion of farmers and the imputation of occupational income for the sons and daughters of farmers.

Alternative occupational income scores

To what extent are our estimates influenced by the choice of using occupational incomes from the year 1900?[4] To test the robustness of our dependent variable, we run our baseline regression again, this time employing occupational income data from the 1930 census.[5] In Figure 6 we present the estimates from our baseline regression using 1900 occupational incomes alongside results from the regression that uses 1930 occupational incomes.

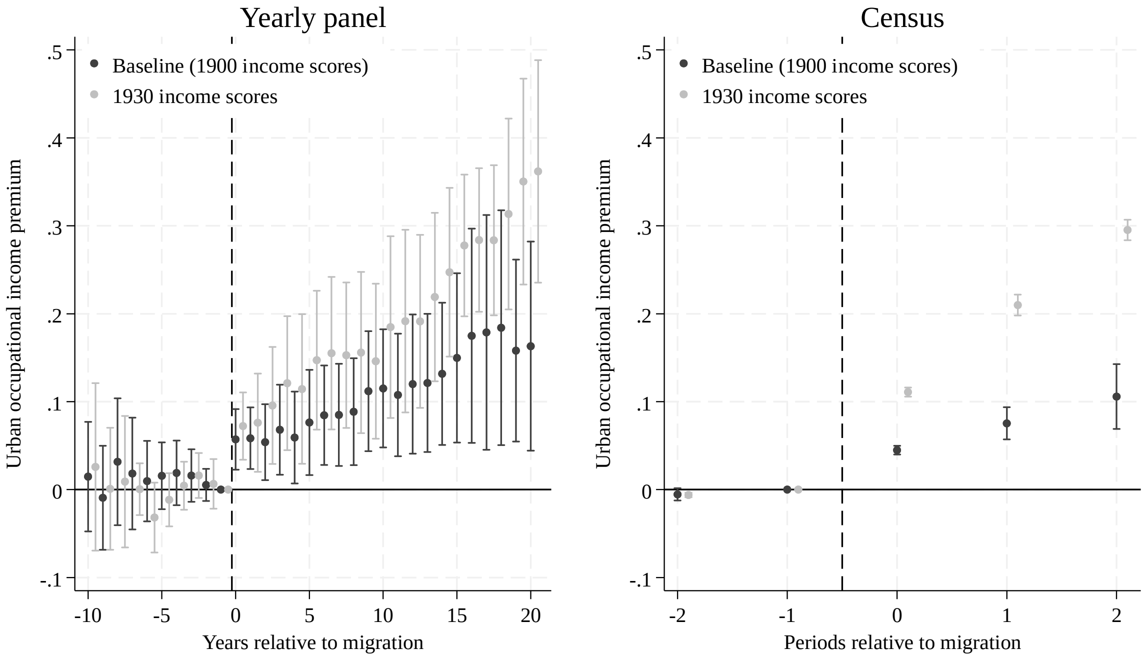
As is evident from the figure, using the alternative income scores for 1930 suggests an even greater impact of moving to an urban area on occupational incomes. The long-run impact is estimated to be around 30 percent in both HISP and the linked censuses. Using the 1930 income scores likewise suggests the absence of pre-migration differences in the occupational income trajectory of migrants and non-migrants. When using the 1930 occupational income scores, the larger impact on long-run occupational income is likely a result of occupations that are more common in cities experiencing greater income growth between 1900 and 1930.

---

[4] The caveats of occupational incomes as a proxy for status and incomes are demonstrated by Feigenbaum (2018) in a study of intergenerational mobility in early twentieth century Iowa. He finds substantially different results depending on whether he uses occupational incomes from 1915 or 1950, and, as a result, leads to vastly different interpretations of historical intergenerational mobility.

[5] The 1930 census includes total income drawn from taxation records for all enumerated individuals. We take the median income by 5-digit HISCO to calculate the income score.

Figure 7: The effect of rural-urban migration on occupational income using 1930 census income data



Source: Andersson (2023) and IPUMS (2020).

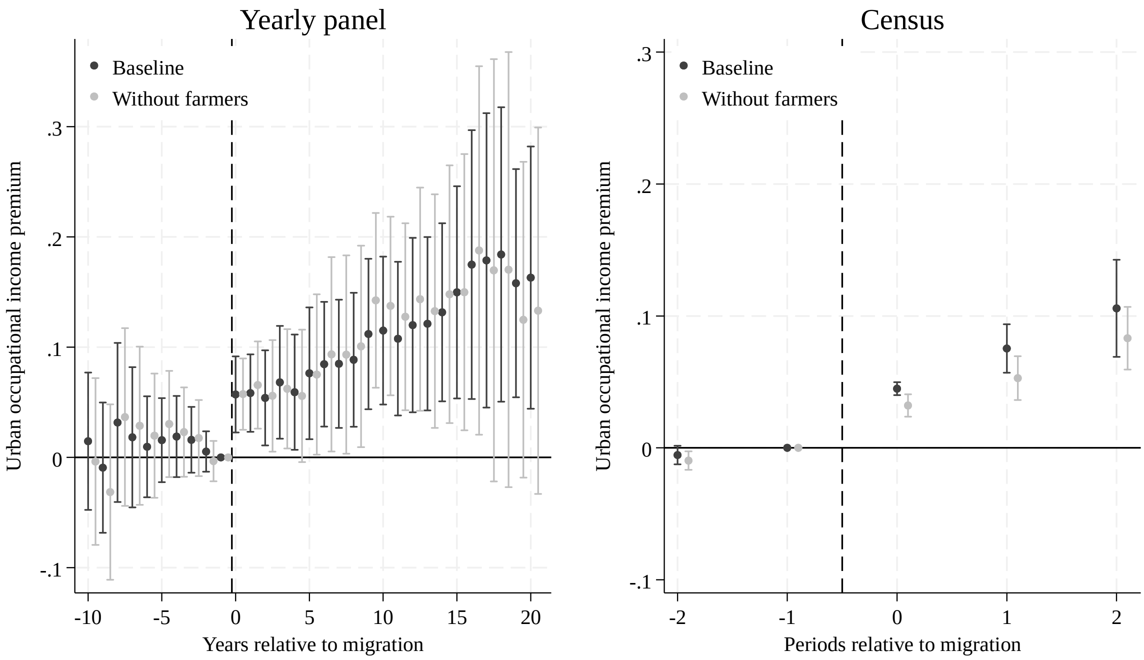
Removing farmers

Another concern pertains to the possibility that our estimates are solely driven by differences in skill attainment between farmers—the most common occupation among rural men—and non-farmers. Given our expectation that farmers are considerably less likely to change their occupation compared to other groups due to heavy investments in immovable property, our results potentially do not truly represent distinctions between urban and rural individuals, but rather show differences between farmers and non-farmers.[6]

To address this concern, we re-run our baseline regression and remove everyone who was ever a farmer during the period under study. The results shown in Figure 7 indicate that the long-run impact is slightly smaller when excluding farmers, but the overall trends are very similar.

[6] Perez (2017) shows in the context of 19th century Argentina that farmers were slow to respond to the opportunities that came with local access to the railway, while he estimates a large effect on the second generation that moved away from farming.

Figure 8: The effect of rural-urban migration on occupational income after removing farmers



Source: Andersson (2023) and IPUMS (2020).

Imputing incomes for sons and daughters of farmers

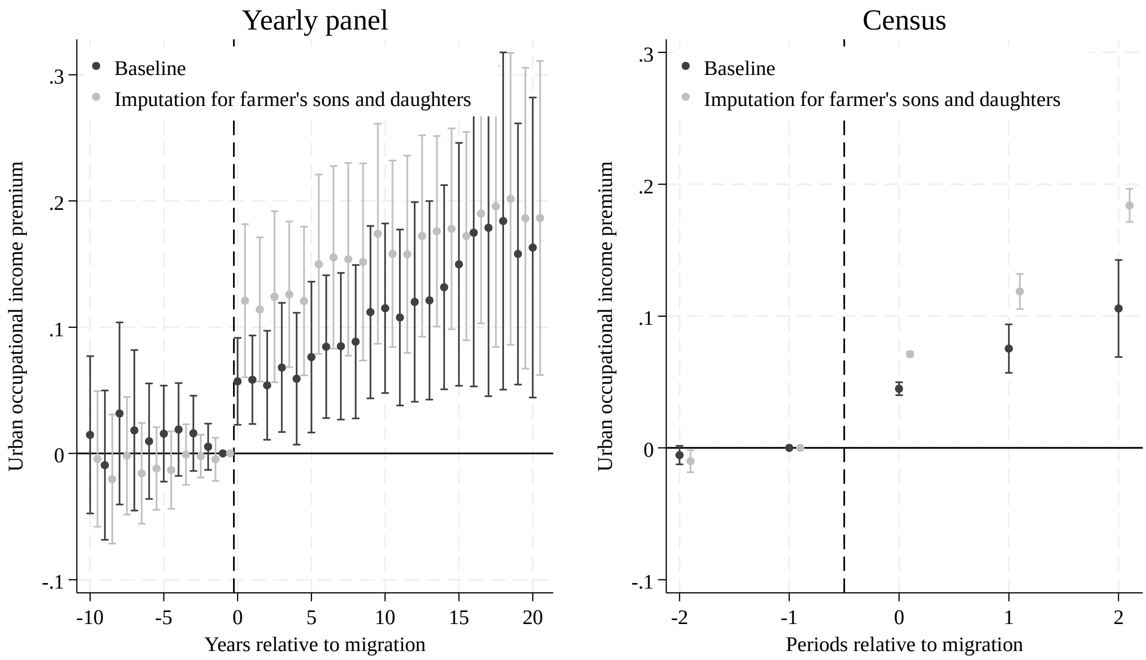
Another concern pertains to the absence of recorded occupational titles for the adult sons and daughters of farmers residing in the parental household. As the Data section outlines, catechetical examination registers—the primary sources for our datasets—did not often document the occupations of individuals in this category. We employ an imputation approach to assess the potential influence of undocumented occupational titles for adult sons and daughters in farming households. Specifically, we impute occupational incomes corresponding to 'farmhands' for sons and 'farm servants' for daughters in farming households who lack recorded occupational titles. These imputed skill levels align with the predominant activities of adult children in farmer households, prevalent during our study period, who performed duties very similar to those of farmhands and farm servants.[7]

We re-run our regression with these imputations and present the results in Figure 8. Notably, the inclusion of imputed occupational incomes yields a larger long-run effect of

[7] See, for example, Morell (2001) for a discussion. Tasks performed on farms were predominately gender separated. For instance, feeding horses and ploughing were performed by a son or a farm servant, while tasks such as raking hay, cooking, and sewing were performed by daughters or farm servants.

rural-urban migration. However, our basic interpretation, emphasizing that urban residence experienced both a static and a dynamic effect, remains unaltered.

Figure 9: The effect of rural-urban migration on occupational income with imputed income scores for the sons and daughters of farmers



Source: Andersson (2023) and IPUMS (2020).

Alternative estimators

A final concern is that our results are dependent on the choice of difference-in-difference estimator. While our baseline estimator from de Chaisemartin and D'Haultfœuille (2023) already addresses the issue of weights that might appear in a regular TWFE model, several other alternatives to the TWFE model have been developed in recent years. To make sure our results are not driven by the particular choice of the de Chaisemartin and D'Haultfœuille (2023) estimator, we also estimate our model using the methods devised by Callaway and Sant'Anna (2021) and Borusyak, Jaravel, and Spies (2021). The results are shown in Figure A1 and Figure A2 in the appendix. The magnitude and trends of the estimates are very similar when using the two alternatives. This suggests that our baseline results are not driven by the particular choice of estimator.

8. Conclusion

In this paper we have investigated the causes of the urban-rural gap in skills that emerge as countries shift from agricultural to non-agricultural activities. While some researchers attribute spatial disparities solely to positive self-selection into urban areas, others have underscored the benefits of living in cities on skills. Notably, the literature on learning in cities postulates that individuals in urban areas experience gains in productivity and human capital as a direct effect of living in an urban environment. However, this debate concerns rich countries in today's developed world. We know much less about the effects of cities on skills at the time when most of today's rich countries began to industrialize around the turn of the nineteenth century and when human capital and technology were less developed.

In this paper, we add significantly to this debate by studying the effects of relocating to an urban environment on skill attainment during industrialization. As a proxy for skills, we employ occupational incomes, a standard approach in the economic history literature, and show that the urban-rural occupational income gap was approximately 30 percent during the entire industrialization phase. We study the causes of this gap by leveraging uniquely detailed historical Swedish longitudinal data and exploit the fact that we can estimate the skills of rural-urban migrants before and after moving. Using a state-of-the-art difference-in-difference estimator with individual and time-fixed effects, which allows for staggered treatment, we address the worry that people are sorted into cities on skills. Moreover, the same estimator allows us to estimate the long-term effects of living in a city on skill attainment.

Our results show that cities did indeed have a positive effect on skill attainment during industrialization. First, conditional on individual-fixed effects, rural-urban migrants did not outperform never-migrants before moving. Their skill trajectories did not differ significantly. Second, we observe an immediate increase in the skills of rural-urban migrants directly upon arriving in an urban environment. We attribute this effect to the static advantages of working in a city relative to the countryside. About half of the effect of living in a city on skills can be explained by the static advantages. Third, as individuals spend more time in an urban area, their skill levels further increase. We attribute this effect to the dynamic advantages of working in a dense environment, in which individuals accumulate experience and, ultimately, skills over time. Moreover, we find that those who possessed the lowest levels of skills when living in the countryside experienced the largest gains from relocating to a city. However, contrary to modern urban economics, we find no differences in skill attainment by agglomeration size. We test this by investigating Stockholm, the only large city in Sweden at the time, separately from other cities. Finally, we run a series of alternative specifications to ensure that our results are robust to the choice of estimator, the measure of skills, discrimination by gender, and career alternatives of individuals in rural areas, which do not alter our interpretation.

As a whole, our results strongly suggest that cities played a pivotal role in the development of human capital during the industrialization period, especially for those individuals who initially possessed relatively low levels of skills. While half of the urban-rural gap in skills can be attributed to unobservable differences in ability between urban and rural individuals, the remaining half is explained by the static and dynamic effects of cities on skills. Our results ultimately suggest that the benefits of living in an urban environment were not exclusive to large cities, and most individuals stood to gain from urban residency.

9. Literature

Abramitzky, R., Boustan, L. P., & Eriksson, K. (2012). Europe's tired, poor, huddled masses: Self-selection and economic outcomes in the age of mass migration. American Economic Review, 102(5), 1832–56.

Allen, R. C. (2009). *The British industrial revolution in global perspective*. Cambridge University Press.

Andersen, M. (2020). Early evidence on social distancing in response to COVID-19 in the United States. *Available at SSRN 3569368*.

Andersson, J. (2023). Migrant selection in and out of cities, Sweden 1870–1940. *Unpublished manuscript.*

Atack, J., Margo, R. A., & Rhode, P. W. (2022). Industrialization and urbanization in nineteenth century America. *Regional Science and Urban Economics*, 94, 103678.

Bacolod, M., Blum, B. S., & Strange, W. C. (2009). Skills in the city. *Journal of Urban Economics*, *65*(2), 136–153.

Bairoch, P. (1988). *Cities and economic development: from the dawn of history to the present*. University of Chicago Press.

Bairoch, P., & Goertz, G. (1986). Factors of urbanisation in the nineteenth century developed countries: a descriptive and econometric analysis. *Urban Studies*, *23*(4), 285–305.

Baum-Snow, N., & Pavan, R. (2012). Understanding the city size wage gap. *The Review of economic studies*, 79(1), 88–127.

Bengtsson, Erik, Jakob Molinder, and Svante Prado. "The Swedish Transition to Equality: Income Inequality with New Micro Data, 1870–1970." Machine-readable data file. Lund, Sweden: Lund University, 2021.

Berry, C. R., & Glaeser, E. L. (2005). The divergence of human capital levels across cities. *Papers in regional science*, *84*(3), 407–444.

Borusyak, K., Jaravel, X., & Spiess, J. (2021). Revisiting event study designs: Robust and efficient estimation. *arXiv preprint arXiv:2108.12419*.

Boustan, L., Bunten, D., & Hearey, O. (2018). Urbanization in American economic history, 1800–2000. *The Oxford Handbook of American Economic History, vol. 2*, 75.

Braghieri, L., Levy, R. E., & Makarin, A. (2022). Social media and mental health. *American Economic Review*, *112*(11), 3660–3693.

Callaway, B., & Sant'Anna, P. H. (2021). Difference-in-differences with multiple time periods. *Journal of econometrics*, *225*(2), 200–230.

Collins, W. J., & Wanamaker, M. H. (2014). Selection and economic gains in the great migration of African Americans: new evidence from linked census data. *American Economic Journal: Applied Economics*, *6*(1), 220–252.

Combes, P. P., Duranton, G., & Gobillon, L. (2008). Spatial wage disparities: Sorting matters!. *Journal of Urban economics*, *63*(2), 723–742.

De Chaisemartin, C., & D'Haultfœuille, X. (2023). Two-way fixed effects and differences-in-differences estimators with several treatments. *Journal of Econometrics*, *236*(2), 105480.

Dribe, M., & Quaranta, L. (2020). The Scanian Economic-Demographic Database (SEDD). *Historical Life Course Studies*, *9*(5), 158–158.

Duranton, G., & Puga, D. (2004). Micro-foundations of urban agglomeration economies. In *Handbook of regional and urban economics* (Vol. 4, pp. 2063–2117). Elsevier.

Eriksson, B. (2015). Dynamic decades: A micro perspective on late nineteenth century Sweden.

Feigenbaum, J. J. (2018). Multiple measures of historical intergenerational mobility: Iowa 1915 to 1940. *The Economic Journal*, *128*(612), F446F481.

Glaeser, E. L. (1999). Learning in cities. *Journal of Urban Economics*, *46*(2), 254–277.

Glaeser, E. L., & Maré, D. C. (2001). Cities and skills. *Journal of labor economics*, *19*(2), 316–342.

Goodman-Bacon, A. (2021). Difference-in-differences with variation in treatment timing. *Journal of Econometrics*, *225*(2), 254–277.

Hatton, T. J., & Williamson, J. G. (2019). Labour Market Integration and the Rural–Urban Wage Gap in History. In *Historical analysis in economics* (pp. 89–109). Routledge.

Henderson, J. V., Nigmatulina, D., & Kriticos, S. (2021). Measuring urban economic density. *Journal of Urban Economics*, *125*, 103188.

Jacobs, J. (1969). *The economy of cities*. New York: Vintage

Keuschnigg, M., Mutgan, S., & Hedström, P. (2019). Urban scaling and the regional divide. *Science advances*, *5*(1), eaav0042.

Kuznets, S. (1955). Economic growth and income inequality. *The American economic review*, *45*(1), 1–28.

Lagakos, D. (2020). Urban-rural gaps in the developing world: Does internal migration offer opportunities?. *Journal of Economic perspectives*, *34*(3), 174–192.

Leeuwen, M. V., Maas, I., & Miles, A. (2002). HISCO: Historical international standard classification of occupations. *Leuven UP*.

Long, J. (2005). Rural-urban migration and socioeconomic mobility in Victorian Britain. *The Journal of Economic History, 65*(1), 1–35.

Lucas Jr, R. E. (1988). On the mechanics of economic development. Journal of monetary economics, 22(1), 3–42.

Lundh, C., & Prado, S. (2015). Markets and politics: the Swedish urban–rural wage gap, 1865–1985. *European Review of Economic History*, *19*(1), 67–87.

Marshall, A. (1890). *Principles of economics.* Macmillan and Company.

Minnesota Population Center (2020). Integrated Public Use Microdata Series, International: Version 7.3 [Dataset]. Minneapolis, MN: IPUMS, 2020.

Morell, M. (2001). Jordbruket i industrisamhället 1870–1945. Det svenska jordbrukets historia, part 4.

Nilsson, L. (1992). *Historisk tätortsstatistik. D. 1, Folkmängden i administrativa tätorter 1800–1970*. Stads-och kommunhistoriska institutet.

Norman, H. (1974). Från Bergslagen till Nordamerika: studier i migrationsmönster, social rörlighet och demografisk struktur med utgångspunkt från Örebro län 1851–1915 (Doctoral dissertation, Acta Universitatis Upsaliensis).

Pérez, S. (2018). Railroads and the rural to urban transition: Evidence from 19th-century Argentina. *Unpublished manuscript.*

Roca, J. D. L., & Puga, D. (2017). Learning by working in big cities. *The Review of Economic Studies*, *84*(1), 106–142.

Schön, L. (2000). *En modern svensk ekonomisk historia: tillväxt och omvandling under två sekel*. (1. uppl.) Stockholm: SNS förlag

Sun, L., & Abraham, S. (2021). Estimating dynamic treatment effects in event studies with heterogeneous treatment effects. *Journal of Econometrics*, *225*(2), 175–199.

The Institute for social sciences (1941). Population Movements and Industrialization: Swedish Counties, 1895-1930. P. S. King & Son, LTD., London

Thomas, D.S. (1941). *Social and economic aspects of Swedish population movements 1750–1933*. New York: MacMillan

Ward, Z. (2022). Internal Migration, Education, and Intergenerational Mobility Evidence from American History. *Journal of Human Resources*, *57*(6), 1981–2011.

William-Olsson, W. (1984). *Stockholms framtida utveckling: Bilaga: huvuddragen av Stockholms geografiska utveckling 1850–1930: bilaga*. Stockholm: LiberFörlag

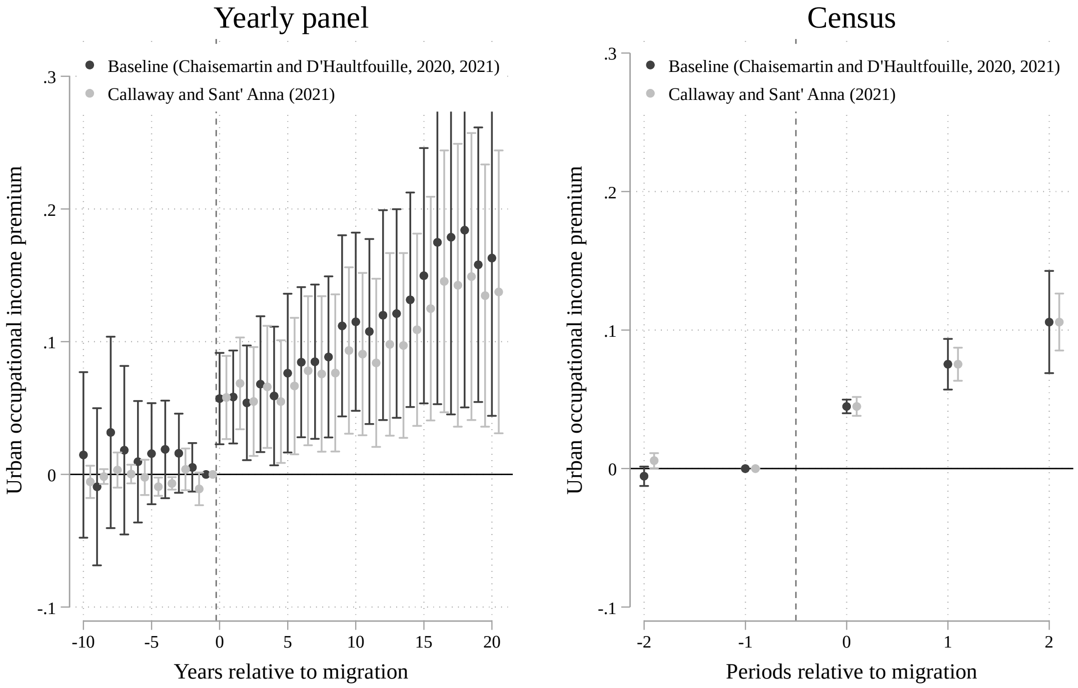
Williamson, J. G. (1988). Migration and urbanization. *Handbook of development economics, 1*, 425–465.

Yankow, J. J. (2006). Why do cities pay more? An empirical examination of some competing theories of the urban wage premium. *Journal of Urban Economics*, *60*(2), 139-161.

Young, A. (2013). Inequality, the urban-rural gap, and migration. *The Quarterly Journal of Economics*, *128*(4), 1727–1785.

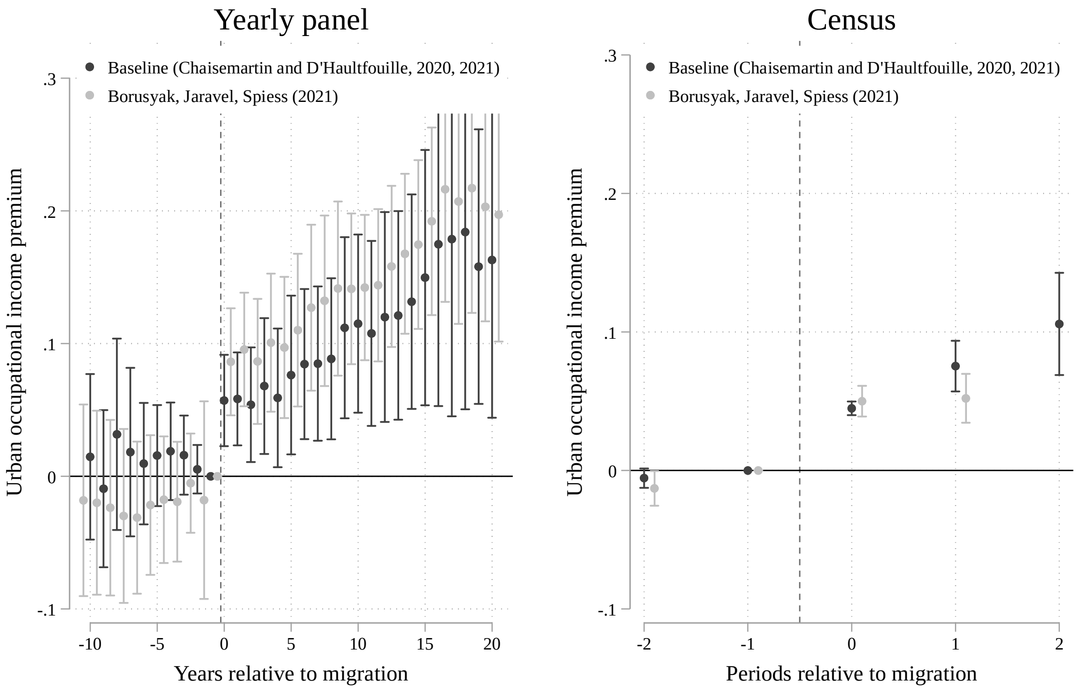
10. Appendix A

Figure A1: The effect of rural-urban migration on occupational income using the Callaway and Sant'Anna estimator



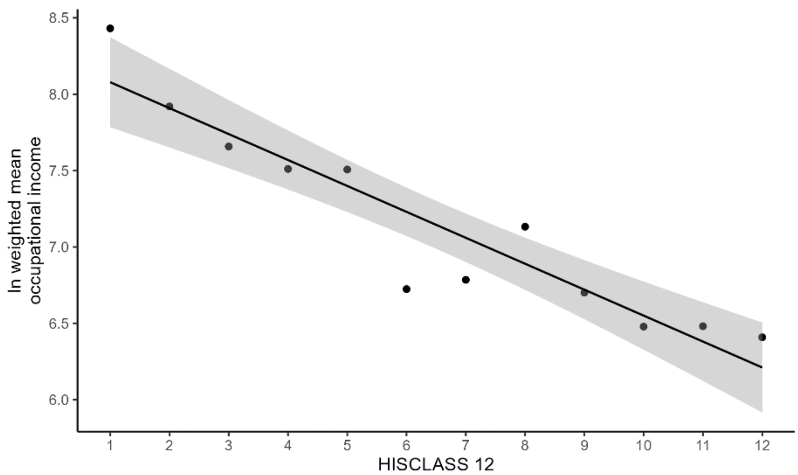
Source: Andersson (2023) and IPUMS (2020).

Figure A2: The effect of rural-urban migration on occupational income using the Borusyak estimator



Source: Andersson (2023) and IPUMS (2020).

Figure A3: Occupational income as proxy for skills. Comparison with the HISCLASS scheme



Code	Description
1	Higher managers
2	Higher professionals
3	Lower managers
4	Lower professionals, clerical and sales personnel
5	Lower clerical and sales personnel
6	Foremen
7	Medium-skilled workers
8	Farmers
9	Lower-skilled workers
10	Lower-skilled farm workers
11	Unskilled workers
12	Unskilled farm workers

Source: Bengtsson et al. (2023) and Berger (2023)

11. Appendix B

Panel dataset

Table B1. Baseline model panel data

	Estimate	SE	LB CI	UB CI	N	Switchers
Effect_0	.0571311	.0175953	.0226444	.0916178	11352	120
Effect_1	.0583726	.0178908	.0233066	.0934386	10371	112
Effect_2	.0539846	.022037	.010792	.0971772	9355	102
Effect_3	.0680619	.0261055	.0168951	.1192287	8832	96
Effect_4	.0591661	.0266784	.0068764	.1114558	8350	93
Effect_5	.0763207	.0304968	.0165469	.1360945	7953	88
Effect_6	.0845634	.0288656	.0279868	.14114	7437	86
Effect_7	.0849181	.0296601	.0267843	.1430519	6964	84
Effect_8	.0885407	.0310013	.027778	.1493033	6632	81
Effect_9	.111945	.034844	.0436507	.1802392	6292	76
Effect_10	.1150556	.0342746	.0478775	.1822338	5942	76
Effect_11	.1076985	.0355581	.0380046	.1773923	5555	71
Effect_12	.1200075	.0403557	.0409103	.1991047	5128	64
Effect_13	.1212525	.0401069	.0426429	.199862	4675	62
Effect_14	.1316483	.0412449	.0508082	.2124883	4286	59
Effect_15	.1497835	.0491062	.0535353	.2460318	3882	55
Effect_16	.1749184	.0622068	.052993	.2968437	3539	54
Effect_17	.1787742	.0681154	.0452681	.3122803	3151	47
Effect_18	.1841053	.0681273	.0505758	.3176349	2855	46
Effect_19	.158029	.0527993	.0545424	.2615155	2566	42
Effect_20	.1630894	.0606581	.0441995	.2819792	2339	38
Average	1.065403	.2923947	.4923092	1.638497	127456	1552
Placebo_1	.0053002	.0093322	-.012991	.0235913	9960	109
Placebo_2	.0159558	.0152031	-.0138424	.0457539	8889	99
Placebo_3	.0189256	.0187663	-.0178563	.0557074	7588	85
Placebo_4	.0156684	.0194102	-.0223755	.0537124	6550	75
Placebo_5	.0096267	.0233472	-.0361338	.0553871	5993	71
Placebo_6	.0182688	.0324334	-.0453007	.0818383	5055	53
Placebo_7	.0316617	.0368028	-.0404717	.1037952	4417	49
Placebo_8	-.0092962	.0301802	-.0684495	.0498571	3596	40
Placebo_9	.0147112	.0317989	-.0476145	.077037	2560	29

Note: This table shows the baseline estimates and confidence intervals from the left-side plot in Figure 2.

Table B2. With controls model panel data

	Estimate	SE	LB CI	UB CI	N	Switchers
Effect_0	.0495135	.0140272	.0220202	.0770069	11352	120
Effect_1	.0519397	.0157692	.0210322	.0828473	10371	112
Effect_2	.0473234	.0190299	.0100249	.0846219	9355	102
Effect_3	.0633223	.0212933	.0215874	.1050572	8832	96
Effect_4	.0538048	.0211851	.0122821	.0953276	8350	93
Effect_5	.06886	.0233218	.0231493	.1145707	7953	88
Effect_6	.0770711	.0309989	.0163132	.137829	7437	86
Effect_7	.0776531	.0319454	.01504	.1402661	6964	84
Effect_8	.0815981	.0330311	.0168571	.1463392	6632	81
Effect_9	.1049105	.0366813	.0330152	.1768058	6292	76
Effect_10	.1082933	.0354949	.0387232	.1778634	5942	76
Effect_11	.1000284	.0361161	.0292409	.1708159	5555	71
Effect_12	.1109762	.0407677	.0310715	.1908809	5128	64
Effect_13	.1121257	.0405409	.0326655	.1915858	4675	62
Effect_14	.1232539	.042193	.0405557	.2059522	4286	59
Effect_15	.1420666	.045077	.0537157	.2304174	3882	55
Effect_16	.167326	.0543852	.060731	.2739211	3539	54
Effect_17	.1713633	.0622881	.0492786	.293448	3151	47
Effect_18	.1763103	.063217	.0524049	.3002157	2855	46
Effect_19	.149651	.0536914	.0444159	.254886	2566	42
Effect_20	.1539813	.0585552	.0392131	.2687494	2339	38
Average	.9880742	.2620192	.4745166	1.501632	127456	1552
Placebo_1	.0056192	.0070039	-.0081084	.0193468	9960	109
Placebo_2	.0168096	.0114131	-.00556	.0391792	8889	99
Placebo_3	.0185903	.0149048	-.010623	.0478036	7588	85
Placebo_4	.0172395	.0163962	-.0148971	.049376	6550	75
Placebo_5	.0105728	.0222816	-.0330992	.0542447	5993	71
Placebo_6	.0169556	.0299713	-.041788	.0756993	5055	53
Placebo_7	.029916	.0337952	-.0363225	.0961546	4417	49
Placebo_8	-.0109545	.0297111	-.0691882	.0472793	3596	40
Placebo_9	.0131184	.0261836	-.0382014	.0644381	2560	29

Note: This table shows the with controls estimates and confidence intervals from the left-side plot in Figure 2.

Table B3. 1930 income scores panel data

	Estimate	SE	LB CI	UB CI	N	Switchers
Effect_0	.0746413	.0204092	.0346393	.1146433	13919	170
Effect_1	.0572365	.024388	.009436	.1050371	12920	159
Effect_2	.0790121	.0259705	.0281099	.1299143	11919	144
Effect_3	.1096002	.0289289	.0528995	.1663009	11197	128
Effect_4	.091404	.0306599	.0313106	.1514973	10384	118
Effect_5	.127158	.0304421	.0674914	.1868246	9752	111
Effect_6	.1397246	.0350678	.0709916	.2084576	9125	108
Effect_7	.1347308	.0325876	.0708591	.1986026	8243	100
Effect_8	.1561751	.0383117	.0810841	.231266	7856	96
Effect_9	.1313298	.0454596	.0422289	.2204307	7219	87
Effect_10	.1446369	.0436213	.0591392	.2301346	6823	86
Effect_11	.1482834	.044275	.0615044	.2350625	6345	79
Effect_12	.1446939	.0532474	.0403289	.2490589	5847	73
Effect_13	.1574233	.0605174	.0388091	.2760375	5135	68
Effect_14	.188833	.0448081	.101009	.2766569	4714	64
Effect_15	.2195604	.0538091	.1140946	.3250261	4264	60
Effect_16	.240292	.0576684	.1272619	.3533221	3867	57
Effect_17	.238363	.0669077	.1072238	.3695021	3455	50
Effect_18	.2746025	.069502	.1383786	.4108265	3224	48
Effect_19	.2791259	.0636024	.1544652	.4037866	2906	44
Effect_20	.2889248	.0694154	.1528707	.4249789	2661	40
Average	1.245895	.2639084	.7286344	1.763155	151775	1890
Placebo_1	.0129749	.0119506	-.0104483	.0363981	12390	152
Placebo_2	.015711	.014125	-.011974	.0433959	10562	128
Placebo_3	.0276369	.0143996	-.0005862	.0558601	9168	107
Placebo_4	.0243419	.0215841	-.0179629	.0666468	7912	91
Placebo_5	-.0021232	.0263525	-.0537741	.0495277	6693	80
Placebo_6	.0365195	.0277069	-.0177861	.0908251	5685	59
Placebo_7	.0336165	.0426102	-.0498994	.1171325	5210	57
Placebo_8	.0008773	.0468745	-.0909968	.0927513	3818	42
Placebo_9	.0406321	.0604934	-.077935	.1591991	2949	31

Note: This table shows the baseline estimates and confidence intervals from the left-side plot in Figure 7.

Table B4. Never farmer panel data

	Estimate	SE	LB CI	UB CI	N Switchers	
Effect_0	.0574355	.0229803	.0123942	.1024769	4948	76
Effect_1	.0656784	.0278306	.0111304	.1202264	4436	71
Effect_2	.0558761	.0368012	-.0162541	.1280064	4058	65
Effect_3	.0622503	.041695	-.019472	.1439726	3816	60
Effect_4	.0557922	.0456524	-.0336865	.1452709	3574	58
Effect_5	.0752031	.0460202	-.0149965	.1654026	3379	55
Effect_6	.0935281	.054719	-.0137212	.2007774	3108	53
Effect_7	.0932491	.0558992	-.0163133	.2028115	2775	51
Effect_8	.1007418	.0558139	-.0086534	.210137	2520	49
Effect_9	.1425024	.0547724	.0351485	.2498563	2371	48
Effect_10	.1374222	.0547226	.0301659	.2446785	2239	48
Effect_11	.1276077	.0538048	.0221503	.2330651	2012	45
Effect_12	.1435106	.0640823	.0179093	.269112	1812	40
Effect_13	.132693	.0689539	-.0024567	.2678426	1619	38
Effect_14	.1480177	.0705195	.0097995	.2862359	1464	35
Effect_15	.1498595	.0739756	.0048672	.2948517	1312	32
Effect_16	.187764	.0826787	.0257138	.3498142	1174	31
Effect_17	.169749	.0809185	.0111487	.3283492	1031	28
Effect_18	.1703006	.0822893	.0090136	.3315877	924	27
Effect_19	.1248595	.0927246	-.0568807	.3065998	797	24
Effect_20	.1331011	.1119484	-.0863178	.3525201	708	22
Average	1.092864	.4755977	.1606925	2.025035	50077	956
Placebo_1	-.0033683	.0079099	-.0188717	.0121351	4284	66
Placebo_2	.0175749	.0253863	-.0321823	.067332	3789	61
Placebo_3	.0229925	.0330494	-.0417843	.0877693	3248	53
Placebo_4	.0303109	.0370375	-.0422826	.1029044	2760	48
Placebo_5	.0197049	.0420577	-.0627281	.1021379	2368	45
Placebo_6	.0286981	.0542094	-.0775523	.1349485	2004	35
Placebo_7	.036607	.0582176	-.0774995	.1507135	1609	33
Placebo_8	-.0314069	.0527663	-.1348288	.072015	1164	25
Placebo_9	-.0037364	.0427274	-.0874821	.0800094	809	19

Note: This table shows the baseline estimates and confidence intervals from the left-side plot in Figure 8.

Table B5. Imputations for sons and daughters

	Estimate	SE	LB CI	UB CI	N	Switchers
Effect_0	.0571311	.0167858	.0242309	.0900312	11352	120
Effect_1	.0583726	.0186738	.0217719	.0949733	10371	112
Effect_2	.0539846	.0223743	.010131	.0978383	9355	102
Effect_3	.0680619	.0256151	.0178563	.1182674	8832	96
Effect_4	.0591661	.0263983	.0074255	.1109067	8350	93
Effect_5	.0763207	.030364	.0168072	.1358341	7953	88
Effect_6	.0845634	.0343807	.0171772	.1519496	7437	86
Effect_7	.0849181	.0346236	.0170559	.1527803	6964	84
Effect_8	.0885407	.0357714	.0184287	.1586527	6632	81
Effect_9	.111945	.0386733	.0361452	.1877447	6292	76
Effect_10	.1150556	.0390305	.0385558	.1915555	5942	76
Effect_11	.1076985	.0385875	.032067	.18333	5555	71
Effect_12	.1200075	.0425315	.0366457	.2033693	5128	64
Effect_13	.1212525	.0434786	.0360344	.2064705	4675	62
Effect_14	.1316483	.0463723	.0407586	.222538	4286	59
Effect_15	.1497835	.0505154	.0507734	.2487937	3882	55
Effect_16	.1749184	.0614858	.0544061	.2954306	3539	54
Effect_17	.1787742	.0679242	.0456429	.3119056	3151	47
Effect_18	.1841053	.0677203	.0513736	.3168371	2855	46
Effect_19	.158029	.0615608	.0373698	.2786882	2566	42
Effect_20	.1630894	.0664539	.0328397	.293339	2339	38
Average	1.065403	.3018762	.4737256	1.65708	127456	1552
Placebo_1	.0053002	.0072826	-.0089736	.019574	9960	109
Placebo_2	.0159558	.0109514	-.005509	.0374206	8889	99
Placebo_3	.0189256	.0131766	-.0069005	.0447516	7588	85
Placebo_4	.0156684	.0147536	-.0132486	.0445855	6550	75
Placebo_5	.0096267	.0154193	-.0205951	.0398484	5993	71
Placebo_6	.0182688	.0198806	-.0206971	.0572347	5055	53
Placebo_7	.0316617	.0235015	-.0144013	.0777247	4417	49
Placebo_8	-.0092962	.0291295	-.0663901	.0477977	3596	40
Placebo_9	.0147112	.0295798	-.0432651	.0726876	2560	29

Note: This table shows the baseline estimates and confidence intervals from the left-side plot in Figure 9.

Table B6. Callaway and Sant'Anna estimator

time	b	se	cil	cih	ci_low	ci_high
-10	-0.0055588	0.0062009	-0.017712	0.006595	-0.0177126	0.006595
-9	-0.0015972	0.0028271	-0.007138	0.003944	-0.0071383	0.0039439
-8	0.0033416	0.0067536	-0.009895	0.016578	-0.0098955	0.0165787
-7	0.0003123	0.0035859	-0.006716	0.007341	-0.0067161	0.0073407
-6	-0.0021499	0.0067776	-0.015434	0.011134	-0.015434	0.0111342
-5	-0.0092488	0.0035254	-0.016159	-0.002339	-0.0161586	-0.002339
-4	-0.0067669	0.0023963	-0.011463	-0.00207	-0.0114636	-0.0020702
-3	0.0038549	0.007995	-0.011815	0.019525	-0.0118153	0.0195251
-2	-0.0109149	0.0062897	-0.023242	0.001413	-0.0232427	0.0014129
-1						
0	0.0579985	0.0159819	0.026675	0.089322	0.026674	0.089323
1	0.0686301	0.0176592	0.034019	0.103242	0.0340181	0.1032421
2	0.0549724	0.0209252	0.01396	0.095985	0.013959	0.0959858
3	0.0660377	0.0234573	0.020062	0.112013	0.0200614	0.112014
4	0.0549408	0.0235709	0.008743	0.101139	0.0087418	0.1011398
5	0.0666497	0.0262376	0.015225	0.118074	0.015224	0.1180754
6	0.0781626	0.0286488	0.022012	0.134313	0.022011	0.1343143
7	0.0757497	0.0299072	0.017133	0.134367	0.0171316	0.1343678
8	0.0764257	0.0302152	0.017205	0.135646	0.0172039	0.1356475
9	0.0933995	0.0319961	0.030688	0.156111	0.0306871	0.1561119
10	0.0906911	0.0311853	0.029569	0.151813	0.0295679	0.1518143
11	0.084092	0.0323413	0.020704	0.14748	0.020703	0.1474809
12	0.0980333	0.0350682	0.029301	0.166766	0.0292996	0.166767
13	0.0971917	0.035526	0.027562	0.166821	0.0275607	0.1668227
14	0.1090746	0.0369383	0.036677	0.181472	0.0366755	0.1814737
15	0.1249833	0.0430234	0.040659	0.209308	0.0406574	0.2093092
16	0.1455068	0.0503479	0.046827	0.244187	0.0468249	0.2441887
17	0.1425875	0.0543513	0.036061	0.249114	0.036059	0.249116
18	0.1491201	0.0551864	0.040957	0.257284	0.0409548	0.2572854
19	0.1347531	0.0504098	0.035952	0.233555	0.0359499	0.2335563
20	0.1375365	0.0543617	0.030989	0.244084	0.0309876	0.2440854

Note: This table shows the baseline estimates and confidence intervals from the left-side plot in Figure A1.

Table B7. Borusyak, Jaravel, and Spies estimator

linc_median	Coefficient	Std. err.	z	P>z	[95% conf. interval]	
tau0	.0863273	.0205758	4.20	0.000	.0459995	.1266551
tau1	.0955879	.0218509	4.37	0.000	.0527609	.1384149
tau2	.0866131	.0240203	3.61	0.000	.0395341	.1336921
tau3	.1007666	.0265399	3.80	0.000	.0487494	.1527838
tau4	.0970691	.0271638	3.57	0.000	.0438291	.1503091
tau5	.1101542	.0293733	3.75	0.000	.0525835	.1677248
tau6	.1271378	.0319101	3.98	0.000	.064595	.1896805
tau7	.1323145	.0327779	4.04	0.000	.068071	.196558
tau8	.1415811	.0334839	4.23	0.000	.0759539	.2072082
tau9	.1413036	.0289575	4.88	0.000	.084548	.1980592
tau10	.1422944	.0279168	5.10	0.000	.0875785	.1970102
tau11	.1440389	.0292593	4.92	0.000	.0866917	.201386
tau12	.1581975	.0309541	5.11	0.000	.0975286	.2188664
tau13	.167713	.0307709	5.45	0.000	.1074032	.2280229
tau14	.1746448	.0324514	5.38	0.000	.1110411	.2382484
tau15	.1922399	.0360585	5.33	0.000	.1215665	.2629133
tau16	.216313	.0432469	5.00	0.000	.1315507	.3010753
tau17	.2071488	.0470786	4.40	0.000	.1148764	.2994212
tau18	.2172121	.0479854	4.53	0.000	.1231626	.3112617
tau19	.2031719	.0440683	4.61	0.000	.1167996	.2895442
tau20	.197204	.0487918	4.04	0.000	.1015739	.2928342
pre1	-.0179122	.0379597	-0.47	0.637	-.0923119	.0564874
pre2	-.0180876	.0368291	-0.49	0.623	-.0902713	.0540961
pre3	-.0199098	.0353977	-0.56	0.574	-.089288	.0494684
pre4	-.0236272	.0337437	-0.70	0.484	-.0897636	.0425092
pre5	-.0298445	.033448	-0.89	0.372	-.0954015	.0357124
pre6	-.0310713	.0292337	-1.06	0.288	-.0883682	.0262256
pre7	-.0216001	.0268378	-0.80	0.421	-.0742013	.0310011
pre8	-.0175648	.0243625	-0.72	0.471	-.0653144	.0301848
pre9	-.0191392	.0230543	-0.83	0.406	-.0643247	.0260463
pre10	-.0051095	.0190808	-0.27	0.789	-.0425072	.0322882

Note: This table shows the baseline estimates and confidence intervals from the plot in Figure A2.

Census dataset

Table B8. Baseline model

	Estimate	SE	LB CI	UB CI	N	Switchers
Effect_0	.0448577	.0024774	.040002	.0497135	404958	6071
Effect_1	.0753504	.0032614	.068958	.0817428	207142	3053
Effect_2	.1057676	.0079394	.0902065	.1213288	62571	1324
Average	.1034647	.003701	.0962108	.1107187	674671	10448
Placebo_1 -	.0054845	.001956	-.0093182	-.0016508	226580	4456

Note: This table shows the baseline estimates and confidence intervals from the right-side plot in Figure 2.

Table B9. Baseline model

	Estimate	SE LB	CI UB	CI	N	Switchers
Effect_0	.0444178	.0027716	.0389854	.0498501	404958	6071
Effect_1	.0743935	.0064945	.0616644	.0871226	207142	3053
Effect_2	.1045658	.0096353	.0856806	.123451	62571	1324
Average	.1023078	.0066325	.089308	.1153075	674671	10448
Placebo_1 -	.005193	.0032361	-.0115358	.0011498	226580	4456

Note: This table shows the with controls estimates and confidence intervals from the right-side plot in Figure 2.

Table B10. 1930 income scores

	Estimate	SE LB	CI UB	CI	N	Switchers
Effect_0	.1109168	.0022463	.106514	.1153196	530917	12804
Effect_1	.2098642	.0035626	.2028816	.2168468	288191	7639
Effect_2	.2952668	.0045653	.2863187	.3042148	106245	4688
Average	.3351998	.0031534	.329019	.3413805	925353	25131
Placebo_1 -	.0061124	.0009609	.0079957	-.004229	310456	8226

Note: This table shows the with controls estimates and confidence intervals from the right-side plot in Figure 7.

Table B11. Only men

	Estimate	SE	LB CI	UB CI	N	Switchers
Effect_0	.0451351	.0035103	.0382549	.0520153	392370	5830
Effect_1	.0755697	.0088311	.0582607	.0928787	203498	2960
Effect_2	.1054485	.0066987	.0923191	.1185778	61883	1302
Average	.1046124	.0072571	.0903884	.1188364	657751	10092
Placebo_1 -	.0056613	.0020575	-.0096941	-.0016285	222328	4355

Note: This table shows the baseline estimates and confidence intervals from the plot in Figure 6.

Table B12. Only women

	Estimate	SE	LB CI	UB CI	N	Switchers
Effect_0	.0385373	.0294322	-.0191498	.0962245	12588	241
Effect_1	.0704414	.016159	.0387697	.102113	3644	93
Effect_2	.1320142	.0633309	.0078855	.2561428	688	22
Average	.0771311	.0340616	.0103705	.1438917	16920	356
Placebo_1	.001489	.0449999	-.0867108	.0896888	4252	101

Note: This table shows the baseline estimates and confidence intervals from the plot in Figure 6.

Table B13. Never farmer

	Estimate	SE	LB CI	UB CI	N	Switchers
Effect_0	.0320934	.0064173	.0195155	.0446713	139459	3582
Effect_1	.0528392	.0082977	.0365758	.0691027	70026	2137
Effect_2	.0830963	.0137419	.0561621	.1100305	21742	1020
Average	.0847247	.013931	.0574199	.1120295	231227	6739
Placebo_1	-.0097084	.0063968	-.0222462	.0028293	78003	2121

Note: This table shows the baseline estimates and confidence intervals from the right-side plot in Figure 8.

Table B14. Imputations for sons and daughters

	Estimate	SE	LB CI	UB CI	N	Switchers
Effect_0	.0448577	.0004659	.0439445	.045771	404958	6071
Effect_1	.0753504	.0075143	.0606224	.0900784	207142	3053
Effect_2	.1057676	.0029342	.1000166	.1115186	62571	1324
Average	.1034647	.0035247	.0965563	.1103731	674671	10448
Placebo_1	-.0054845	.0013353	-.0081017	-.0028672	226580	4456

Note: This table shows the baseline estimates and confidence intervals from the right-side plot in Figure 9.

Table B15. All except Stockholm

	Estimate	SE	LB CI	UB CI	N	Switchers
Effect_0	.0482703	.0134927	.0218247	.0747159	375088	1199
Effect_1	.0799011	.0063157	.0675222	.0922799	193141	859
Effect_2	.1006028	.001125	.0983978	.1028078	58252	495
Average	.1452302	.0083984	.1287694	.161691	626481	2553
Placebo_1	-.0288246	.0009678	-.0307215	-.0269277	209728	563

Note: This table shows the baseline estimates and confidence intervals from the plot in Figure 4.

Table B16. Below median occupational income

	Estimate	SE	LB CI	UB CI	N	Switchers
Effect_0	.0715041	.0004766	.0705699	.0724382	219896	1790
Effect_1	.1300564	.004295	.1216382	.1384745	125908	933
Effect_2	.1858244	.0267021	.1334883	.2381604	49011	466
Average	.1823719	.005043	.1724877	.1922561	394815	3189
Placebo_1	-.0087312	.0034985	-.0155883	-.0018741	139897	1870

Note: This table shows the baseline estimates and confidence intervals from the plot in Figure 5.

Table B17. Above median occupational income

	Estimate	SE	LB CI	UB CI	N	Switchers
Effect_0	.0382416	.0019975	.0343264	.0421567	185060	4280
Effect_1	.0596113	.0015503	.0565728	.0626498	81234	2120
Effect_2	.0812803	.0318496	.018855	.1437056	13560	858
Average	.0824069	.0035481	.0754526	.0893612	279854	7258
Placebo_1	-.0065456	.0064379	-.0191639	.0060728	86683	2586

Note: This table shows the baseline estimates and confidence intervals from the plot in Figure 5.

Table B18. Callaway and Sant'Anna estimator

Coefficient	Std. err.	z	P>z	[95% conf. interval]
g2				
t_1_2 .0602606	.0073587	8.19	0.000	.0458377 .0746835
t_1_3 .0681404	.0080016	8.52	0.000	.0524577 .0838232
t_1_4 .1057676	.0104746	10.10	0.000	.0852379 .1262974
g3				
t_1_2 -.0039494	.0051371	-0.77	0.442	-.014018 .0061192
t_2_3 .0519197	.0072486	7.16	0.000	.0377127 .0661267
t_2_4 .0836418	.0092273	9.06	0.000	.0655567 .1017269
g4				
t_1_2 .0086283	.0037084	2.33	0.020	.0013598 .0158967
t_2_3 .0110256	.0032135	3.43	0.001	.0047272 .017324
t_3_4 .030478	.0044067	6.92	0.000	.0218412 .0391149
Number of obs = 646,465				

Note: This table shows the baseline estimates and confidence intervals from the plot in Figure A1.

Table B19. Borusyak, Jaravel, and Spies estimator

linc_median	Coefficient	Std. err.	z	P>z	[95% conf. interval]
tau0	.0500126	.0056662	8.83	0.000	.038907 .0611183
tau1	.0520515	.009007	5.78	0.000	.0343982 .0697048
tau2	0	(omitted)			
pre1	-.0129078	.0064138	-2.01	0.044	-.0254787 -.000337
Number of obs = 24,485					

Note: This table shows the baseline estimates and confidence intervals from the plot in Figure A2.