Melting Opportunities: Technological Change and Labor Market Perspectives*

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Abstract

Icemen were common in U.S. cities until refrigerators began to enter homes en masse. I study the long-run consequences of this technology shock for incumbent ice retailers and their descendants. I find that the general spread of electric refrigeration increased the likelihood of incumbents not only to leave ice retailing, but also to change occupations. These new occupations were often lower paid. Differentiating by fathers' self-employment status reveals that business owners adapted within the ice retailing industry, while dependent employees sought their fortunes outside of it. The technological shock had intergenerational spillover effects, particularly for younger cohorts of sons who faced a tradeoff between labor market participation and school attendance, leading to an average decline in school attendance rates.

Keywords: Iceman, Electric Refrigerator, Technological Change, Labor Market

JEL Codes: D31, J24, J62, N72, N2, O14

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1 Introduction

The discourse on the consequences of technological progress for the labor market remains a central theme in ongoing economic debates (Mokyr et al., 2015). More recently, the adverse effects of automation, robotics and artificial intelligence have further fueled these discussions (Autor, 2022; Autor et al., 2024; Acemoglu et al., 2022). Although much of the literature has analyzed the aggregate impacts of technological shocks, it does not address the individual-level adjustment process, which can entail significant economic costs (Bessen et al., 2023). It is only recently that empirical work has focused on the individual-level consequences, emphasizing the role of factor-biased technological change in determining the winners and losers in the labor market (Bessen et al., 2023; Braxton and Taska, 2023; Cuccu and Royuela, 2022; Feigenbaum and Gross, 2024; Humlum, 2022; Kogan et al., 2023). Since research has primarily focused on incumbent workers, little is known about potential spillovers effects on family members and whether they also adjust after a technology shock.

To address this gap in the literature, I examine the spread of electric refrigerators in U.S. households as a technological shock that replaced manual labor in ice retailing during the 1930s (Anderson, 1953; Gordon, 2016; Rees, 2013, 2018). Accordingly, I analyze both the individual-level effects and intergenerational consequences of a shock that disrupted an entire industry. Regardless of skill level, this shock was one of labor substitution rather than labor augmentation. Furthermore, I focus on a industry with a significant percentage of self-employed individuals, offering a novel perspective of the interaction between business ownership and the response to technical change.[1]

Iceboxes were initially used for refrigerated food preservation, which required regular replenishment of ice blocks and delivery by iceman. With the advent of electric refrigeration in the 1930s, such as the Monitor Top, ice blocks became obsolete, and the ice retail industry faced declining demand, leading to its dissolution (Rees, 2013, 2018). In my analysis, I exploit the heterogeneous diffusion of these new electric refrigerators across U.S. counties during the 1930s in a triple difference-in-differences (3DiD) framework. I do so by comparing the outcomes of ice retailing workers and their descendants relative to the outcomes of other workers in different industries (first difference) in counties with high and low electric refrigeration adoption rates (second difference) before and after 1930 (third difference). In my analysis, I evaluate the consequences along several dimensions, including changes in occupation and industry, income, self-employment, migration, housing and educational outcomes

[1] In the 1930 U.S. census, 27% of individuals in the wholesale and retail industry were self-employed, a number exceeded only by agriculture at 61%. Author's calculations based on the full count U.S. Census of Population (Ruggles et al., 2024).

of sons.[2] A potential threat to my identification strategy is that regional economic trends might correlate with the regional spread of electric refrigerators. In particular, the aftermath of the Great Depression may have influenced the purchase of electric refrigerators. However, this is not a major concern in my analysis, as the 3DiD approach allows me to control for confounding regional economic trends that might otherwise bias the estimates. Furthermore, I show that the effects of the Great Depression did not have a differential impact on the ice retail industry relative to other industries.

This study provides several insights into the intergenerational labor market consequences of technological change. First, the likelihood of leaving the ice retailing industry increased by about 11 percentage points on average due to higher rates of electric refrigerator ownership. Associated with a higher rate of industry switching, incumbents experienced a shift in their occupational roles, resulting in a lasting decline in earnings, estimated at 12%.

Second, I analyze who was most affected and how they adjusted. Younger fathers primarily bore the burden in terms of industry and occupational shifts and diminished earnings, while older incumbent fathers left the labor force after a decade. Although the advent of electric refrigeration posed a significant challenge to those involved in ice retailing, not everyone decided to change their industry or occupation. Furthermore, distinguishing by self-employment status reveals insight into various adjustment mechanisms. Self-employed ice retailers tended to exit the industry entirely or transition to a dependent employee role within the same industry. Conversely, dependent employees sought opportunities outside of the ice retailing industry. Both adjustment strategies lead to a downgrading of occupational status and a reduction in income.

Third, the evidence suggests negative spillover effects, particularly for younger cohorts. Sons between the ages of 6 and 9 years appear to face a tradeoff between labor market participation and school attendance 10 years later, resulting in an average reduction in school attendance rates of 20 percentage points. This effect is particularly pronounced if the father was previously self-employed but subsequently gave up his business, suggesting that economic constraints compelled younger children to contribute to the household income. For older cohorts between the ages of 10 and 17 years, I do not observe any systematic affects on their labor market prospects, nor does the observation of the father's business model becoming obsolete discourage sons from becoming self-employed.

My empirical analysis most closely relates to an emerging body of literature that evaluates historical economic case studies to gain insight into the intergenerational consequences of technological change and automation. Cockriel (2023) considers the de-skilling of shoe-

[2]The rationale of focusing on fathers with sons is that links across census years can be established primarily for men, as women had often changed their surnames after getting married.

makers due to the McKay stitcher, a sewing machine for shoe soles. The former skilled craftsmen contended with automation, leading to a decline in wages for themselves and their sons. French (2022) focuses on the mechanization of U.S. agriculture. While farmers and their sons experienced an increase in income and employment opportunities, unskilled agricultural workers left the industry, settling for employment in other industries with lower wages. Contrary to focusing on men, Feigenbaum and Gross (2024) examine the adoption of mechanical switching by AT&T between 1920 and 1940, leading to a significant displacement of women working in telephone operation. Nevertheless, the study underscores the role of the reinstatement effect, which led to the emergence of new employment opportunities in sectors beyond the initially affected industry. Ager et al. (2023) find positive labor market effects for displaced women working in agriculture after the introduction of milking machines. They explain their findings by the improved labor allocation of women who migrated to cities, which had positive spillover effects for their children. The four studies mentioned above focus on shocks that have displaced particular demographic groups or occupations. I contribute to the literature by focusing on a technological shock that disrupted an entire industry. This approach allows for a more comprehensive evaluation, as I am able to document that the same negative demand shock can lead to different adjustment strategies.

The occupational choices of different generations are often highly correlated (Long and Ferrie, 2018), which may contribute to the persistence of inequalities by limiting social and economic mobility (Greenberg et al., 2024). High correlation across generations is also evident in terms of self-employment and entrepreneurship (Giménez-Nadal et al., 2022) and relates to business inheritance (Holtz-Eakin et al., 1994), knowledge sharing (Hvide and Oyer, 2017) or the transmission of personality traits (Li and Goetz, 2019).[3] There is evidence that economic shocks may disrupt the occupational and industrial persistence between fathers and sons (Bütikofer et al., 2022; Cockriel, 2023). However, less is known about the impact of a disruptive shock on the labor market decisions of sons whose father is self-employed. This paper sheds light on this issue by evaluating the consequences of electric refrigeration.

This paper also contributes to the extant literature on job displacements and their intergenerational consequences as a result of firm closures. The evidence points to negative effects in employment and wages (Jacobson et al., 1993; Couch and Placzek, 2010). Layoffs of fathers can have negative spillover effects at home, negatively affecting children in terms of human capital development and labor market outcomes (Oreopoulos et al., 2008; Stevens and Schaller, 2011; Rege et al., 2011), although the overall evidence remains inconclusive

[3]In a related study, Ager et al. (2021) investigates the abolition of slavery in the United States following the Civil War, resulting in a significant decline in the wealth of those who owned slaves. Marriage networks and connections to other elite families helped families recover from the wealth shock within two generations. Entrepreneurship was of minor importance for wealth recovery.

(Hilger, 2016; Jensen et al., 2023). The majority of these studies have focused on relatively brief periods following displacement. Evaluating an historical setting using full count census information allows for a more comprehensive evaluation of long-run consequences (Aizer et al., 2025).

Finally, this paper contributes to the literature on technological change and its effects on the labor market. This includes literature related to automation (Autor, 2015, 2022), such as robotics (Acemoglu and Restrepo, 2020; Dauth et al., 2021), artificial intelligence (Acemoglu et al., 2022), and historical cases of technological change. The introduction of steam-powered engines (Atack et al., 1980; Hornbeck et al., 2024), electricity (Fiszbein et al., 2020; Goldin and Katz, 1998) and related automation in manufacturing (Atack et al., 2019) and computer numerical control machinery (Boustan et al., 2022) are notable examples. The focus on electric refrigeration complements this literature by providing new evidence for the retail industry.

This paper proceeds as follows: Section 2 reviews the historical context of the retail ice industry. Section 3 describes the data sources and structure of the sample. The empirical analysis is divided into three parts. To anticipate possible effects on fathers and their sons, it is crucial to understand how electric refrigeration affected ice retailing at the aggregate level (implicit first stage). Therefore, Section 4 focuses on the aggregated effects to show that the introduction of electric refrigeration had a meaningful economics effect. Following this analysis, Section 5 focuses on incumbent fathers, while Section 6 analyzes the intergenerational consequences for sons. Section 7 summarizes the previous results and concludes with economic implications.

2 Historical Background

Before the introduction of electric refrigeration into U.S. households, those seeking to preserve food through refrigeration were forced to use iceboxes. They typical consisted of two components: a storage compartment for food and a compartment for ice blocks. The ice block then cooled the stored food by extracting heat through the process of melting. As a result, the ice blocks had to be replenished on a regular basis, usually by icemen (Rees, 2018, p. 63).

Initially, the natural ice industry was the primary source of ice blocks for homes. In most cases, they sourced it from frozen rivers and seas during the winter, marking the onset of the cold chain.[4] These blocks were subsequently transported to ice houses located at lakes

[4]Imports of ice, such as from Norway, were not uncommon to complement the ice supply (Rees, 2013, p. 26).

and riversides. Ice houses permitted the year-round supply of ice for urban areas and their surrounding regions. Utilizing rivers for transportation further facilitated the movement of ice blocks. In urban centers, ice dealers received ice deliveries and distributed them to their customers (Rees, 2018, pp. 46-47).[5]

The concept of mechanical refrigeration has been evident since at least the 1840s.[6] However, it was not until the 1860s that the industry utilized mechanical refrigeration to produce ice commercially (Anderson, 1953, p. 86). Given the dependence on local natural conditions, the first ice manufacturers were located primarily in the southern U.S., where the natural ice industry could not meet demand due to its inherent limitations. Several shortcomings in the early days of mechanical ice production - such as uncompetitive pricing due to energy intensity in the early stages, inferior quality, and public skepticism - hindered a more rapid dominance over natural harvesting. For example, while 77 ice plants were in operation in 1900, none were in Michigan or Wisconsin (see Figure B.1 in the Appendix). Gradual improvements led to a northward expansion by the 1920s, resulting in the dissolution of the natural ice industry, the first casualty of mechanical refrigeration. The mechanical ice industry emerged as the primary provider of ice blocks to retail dealers, who subsequently delivered these blocks to the end consumer (Rees, 2018, pp. 29-31).

In the early 20th century, icemen were common in urban American settings, transporting ice in their ice wagons or, in later years, ice cars.[7] Most worked for ice delivery companies, though a significant share were self-employed.[8] As the ice delivery companies received their products from ice manufactures, they were integral to the local ice supply chain.[9] Icemen would then collect ice from nearby ice factories or ice houses and follow their assigned route to deliver the ice locally to customers. Customers either pre-ordered a regular delivery on certain days or placed a card in their window to indicate a desire for ice. Icemen then took blocks of ice to the customers, which often included packing and placing it in their homes.

[5]In addition to end users such as households, hotels, bars, and breweries, the meatpacking industry was intrigued by refrigeration for transporting meat. As a result, they integrated cooling into their supply chain by developing their own refrigeration infrastructure. This process involved ice harvesting or manufacturing, owning ice houses near railroads, and improving the insulation and refrigeration of ice cars that transported meat across states. For an overview of the role of the meatpacking industry, see Anderson (1953), Rees (2013) or Rees (2018). For an economic analysis on the impact of refrigeration on the meatpacking industry, see Huang (2021). In contrast, this paper focuses on the labor market impact of refrigeration on the ice retail industry.

[6]In 1834, Jacob Perkins developed the first operational refrigeration system (Rees, 2013, p. 37).

[7]The vertical integration of the supply chain, including the local distribution of ice, was more common during the natural ice era but experienced a shift with the adoption of ice manufacturing. Ice producers were no longer involved in the redistribution process (Rees, 2018, p. 48).

[8]In the 1930 U.S. census, 19% of individuals in the fuel and ice retail industry were self-employed. Author's calculations based on the full count U.S. Census of Population (Ruggles et al., 2024).

[9]A significant number of ice dealers also engaged in coal delivery during the winter months, addressing the deficit in ice demand during this period. (Rees, 2013, p. 79)

This cold chain structure reflected the situation of ice distribution in many U.S. cities, just before electric refrigeration was about to change it fundamentally (Rees, 2018, pp. 48-49).

The first forerunners of the modern refrigerator entered households in the 1910s. In the first models, refrigeration units were often installed in iceboxes, which were not intended for this purpose and could not be scaled for mass production (Rees, 2013, pp. 138-139). In addition, early electric refrigerator designs were very expensive and lacked key qualitative features, resulting in low adoption within U.S. households in the 1910s and early 1920s. Loud electric motors, the inability to reach and maintain a low temperature, high maintenance costs and incidents of intoxication due to the release of refrigerant gases all led to widespread public skepticism in the early stages (Rees, 2018, p. 79).

Many of these shortcomings were overcome after the introduction of several new refrigerator models in the second half of the 1920s, the most prominent being General Electric's (GE) Monitor Top model (see Figure B.2 in the Appendix for an illustrative example). Introduced in 1927, it had the appearance of a modern refrigerator, could be quickly set up by plugging it into the electrical outlet and could even make its own ice.[10] In addition to its technological advantages, a sharp drop in price played a role in its widespread popularity in U.S. households and accelerated sales across the country. Backed by a major GE advertising campaign, sales of the Monitor Top soared from 50,000 in 1929 to one million units in 1931 (Rees, 2018, pp. 80-81). Other competitors followed, such as Sears' Coldspot, which was available by mail order from the popular Sears catalog (Gordon, 2016, p. 121).

Figure 1 plots the trends in ownership rates and average prices of electric refrigerators (in 1947-49 prices) from 1920 to 1960. Prior to 1930, U.S. electric refrigerator use was not common, with approximately 9% of households owning a refrigerator. However, the mass production of refrigerators such as the Monitor Top led to a sharp decline in average prices, from approximately $600 in 1925 to $275 in 1935.[11] This decline made refrigerators far more affordable for the average household during this period. The Bureau of Labor Statistics (1938) estimated an annual median family household income of about $2030 from 1935 to 1936.[12] Thus, after the price drop, the cost of electric refrigerators fell from about 30% to 14% of median household income. This decline may partially explain why, despite the Great Depression, about 30% of all U.S. households owned an electric refrigerator in 1935, rising to

[10] Alternatives such as the Kelvinator required a hole in the ground for connection to the refrigeration system one floor below (Rees, 2013, p. 151).

[11] The first Monitor Top model retailed for $525 in 1927 (Rees, 2018, p. 81).

[12] According to the Bureau of Labor Statistics (1938), the median household income was approximately $1,160 from 1935 to 1936. To ensure comparability with the price data for refrigerators, I adjusted the household income to the 1948 price level. To do so, I utilized the historical consumer price index, which is available at https://www.minneapolisfed.org/about-us/monetary-policy/inflation-calculator/consumer-price-index-1913- (accessed March 15, 2025).

56% in 1940, and 85% in 1950. In addition to the average price decline, government programs that provided loans for appliances, such as the National Housing Act, further contributed to increased sales of electric refrigerators (Rees, 2013, p. 165). The only interruption in the growth in ownership of electric refrigerators occurred during U.S. involvement in World War II (WWII). Also of note is the relationship between household access to electricity and refrigerator ownership, which is a necessary condition for the operation of electric refrigeration systems. General access to electricity did not limit the diffusion of electric refrigerators, as more households had access to electricity than owned a refrigerator. This gap closed during the 1950s.

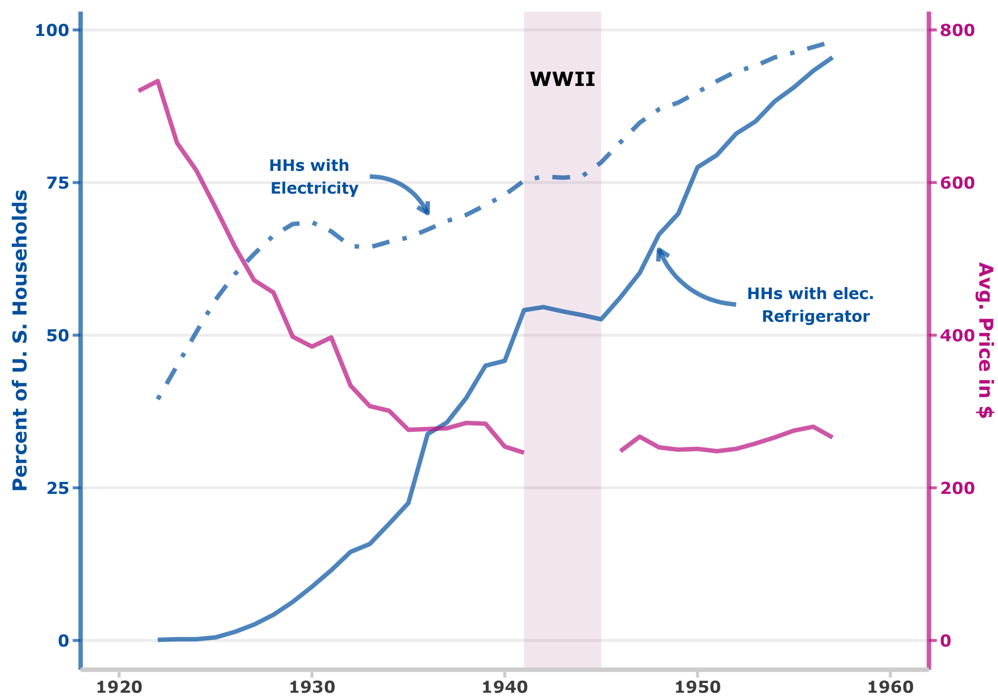


Figure 1 – Distribution of electric refrigerators and corresponding average prices

Notes: The graph illustrates the number of American households with access to **electricity** or **electric refrigerators** on the left blue y-axis. The right y-axis shows the **real average price** of electric refrigerators based on prices from 1947-1949. The pale red area corresponds to U.S. involvement in World War II. *Source: Table 1 from Miller (1960).*

These developments impacted the market for classical iceboxes, as illustrated in Figure 2. Sales fell from 1926 onwards, with a marked acceleration of the decline in 1930. This was also when sales of electric refrigerators finally overtook ice boxes, marking a turning point in the history of the ice retailing industry. By 1934, sales of iceboxes were a quarter of the level of a decade earlier. During the 1950s, ice retailing had disappeared and were no longer relevant for U.S. households (Rees, 2018, p. 93).

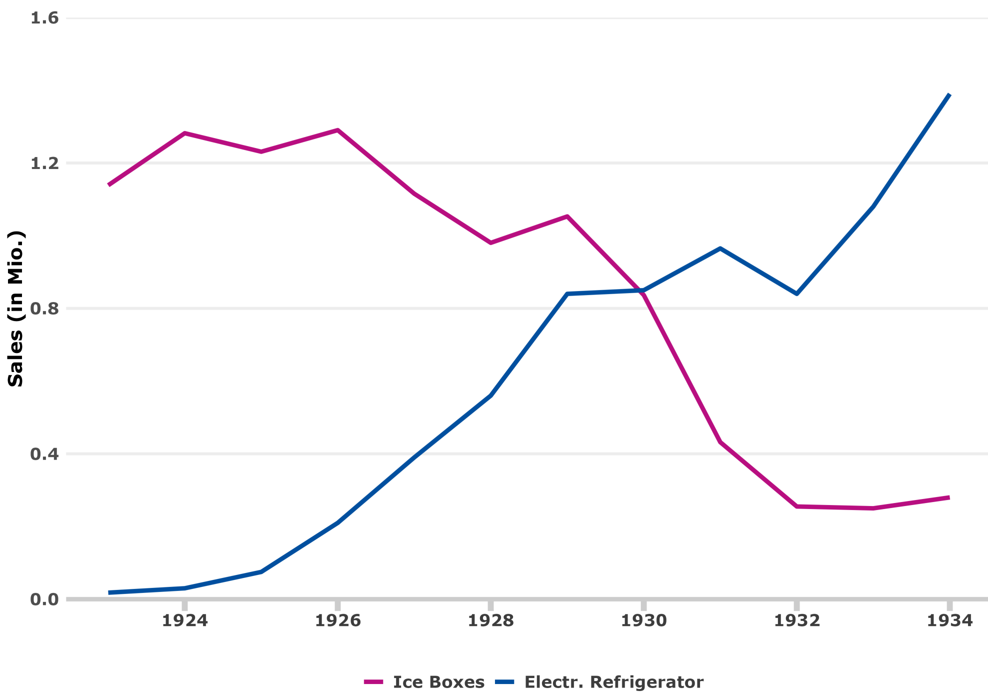


Figure 2 – Sales of Iceboxes and Electric Refrigerators (1923-1934)

Source: Table 4, p. 484 from American Society of Refrigerating Engineers (1937).

3 Data

The datasets I use provide a measure of the diffusion of electric refrigerators and full count information from the decennial census. Based on this data, I construct three different samples. The first aggregates industry information at the county level to identify macroeconomic impacts of the technological shock. The second includes information at the individual level on fathers linked across census waves to obtain a longitudinal structure. The third is like the second, but only accounts for the sons of incumbent fathers.

3.1 Data on the Spread of Electric Refrigerators

To capture the distribution of electric refrigerators, I use the proportion of households with refrigerators at the county level from the 1940 Census of Population and Housing (Haines and ICPSR, 2005). The idea is to interpret the geographic distribution of electric refrigerators in 1940 as an exposure variable for incumbent workers in the ice retail industry in the 1930s. Census data prior to 1940 do not provide county-level information on ownership of electric refrigeration. However, prior to 1930, electric refrigerators were not widely present in American households, as documented in Section 2. In 1930, only 8.8% of U.S. households owned an electric refrigerator (Miller, 1960). Thus, the percentage of households using electric refrigerators in 1940 serves as a proxy indicator for the shift in refrigerator utilization during the 1930s, as the numbers were likely in the low single digits for most counties prior to this period.

Figure 3 illustrates the distribution of U.S. households that owned an electric refrigerator in 1940, organized into deciles. The map highlights notable heterogeneity in electric refrigerator ownership rates across the country. Households on the West and Northeast coasts as well as in the Rust Belt area tend to be early adopters. However, southern counties such as in Arizona, Texas, and Florida also have a high percentage of households with electric refrigerators, likely due to the warmer climates.

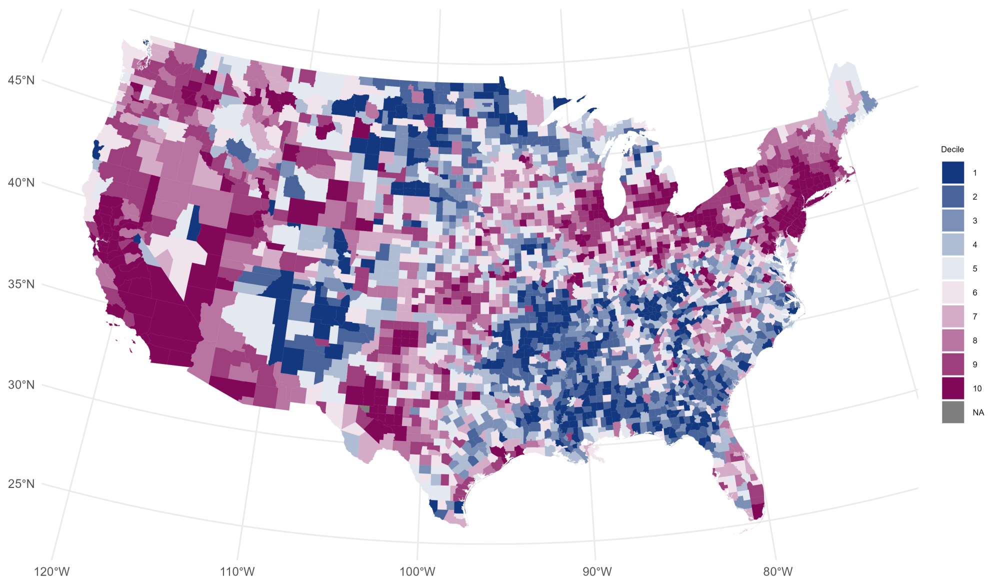


Figure 3 – Share U.S. Households with Electric Refrigerators

Notes: County-level data from the 1940 Census of Population and Housing (Haines and ICPSR, 2005) shows the percentage of households with an electric refrigerator (U.S. mainland). The corresponding decile is displayed on the map. The range between the 1st and 10th decile is 61 percentage points (10% to 71%).

Figure B.3 in the Appendix shows the (residualized) correlation between the share of households with electric refrigerators and other county characteristics. Adoption is highly correlated with access to electricity, although this reflects a necessary rather than sufficient condition, as discussed in Section 2. In general, counties with higher rates of electric refrigeration adoption tend to have a larger urban population, a more educated male population, higher median home values, and more people employed in manufacturing.

3.2 Linked Census Data

This study utilizes the IPUMS full-count census data from 1900 to 1940 (Ruggles et al., 2024). The data provides individual-level information on socioeconomic outcomes, including age, sex, race, birthplace, and labor market variables, which can be linked across census waves (Abramitzky et al., 2021). Most importantly, the dataset contains standardized information about the industry in which a person worked, based on the 1950 Census Bureau industrial classification.[13] This allows me to identify individuals who had been exposed to industry-level technological changes in refrigeration. The most important aspect of this study pertains to the fuel and ice retailing industry (industry code 697). I used the transcribed string information from the original manuscript to further distinguish between the two industries.[14] The string industry information provided by IPUMS is only available through 1930. However, this limitation does not hinder the identification of affected individuals before the systematic spread of electric refrigerators during the 1930s. For a more detailed explanation of how I used the string information, see Section A.1 in the Appendix. Based on this information, I constructed three datasets to assess various aspects of refrigeration adoption, which I describe below.

3.3 Aggregated Data on Local Outcomes

The first part of the empirical analysis focuses on whether significant macroeconomic effects are evident. I regard this part as an implicit first stage to anticipate possible effects on fathers and their sons on the individual level. Therefore, I aggregate the male labor force between the ages of 18 and 60 into an industry-county panel, which measures absolute counts to approximate the industry size.[15] Based on these counts, I calculate per capita growth rates of the industry size, which represent my main macroeconomic measure to describe industry dynamics. The analysis considers the entire labor force and does not restrict the sample to individuals employed during the census survey due to the following two reasons. First, there is no information available on employment status for 1900 and 1920. Excluding these census years would significantly limit the subsequent empirical analysis in a difference-in-differences (DiD) setting.[16] Second, occupation and industry information in the census

[13] Ruggles et al. (2024) harmonized individual-level industry information across census years to the 1950 classification scheme.

[14] The transcribed string information of the original record on the census form are not openly accessible. I obtained restricted access to 20% of each census wave observations, which was sufficient to classify all individuals within the fuel and ice retailing industry.

[15] The panel includes 126 industries and 3,095 counties. I do not include agriculture, fishing, forestry, construction and mining.

[16] Excluding those years would not allow a proper evaluation of possible pre-trends.

generally refer to current or most recent employment. Consequently, individuals who self-identify as belonging to a particular industry but are currently unemployed may reflect some short-term fluctuations. Therefore, the total number of people associated with an industry should yield information about the structural importance of an industry in a given region over time.[17]

One limitation of the aggregate analysis is the lack of industry-specific string information for 1940. As a result, it is not possible to separate fuel and ice retailing into two distinct industries for the entire analysis period. Therefore, I evaluate the aggregate impact for both industries together. When interpreting the results, it is important to note that the estimated coefficients likely represent a lower bound, as the observed changes relate to a base value that is too large.

Data measuring the consequences of the Great Depression from Fisback et al. (2005) further augments the dataset for aggregate outcomes. More specifically, I incorporate 1929-1933 growth rates in retail sales as a measure of the severity of the Great Depression at the county level. A series of government grants followed the Great Depression to mitigate the economic consequences. These grants may have influenced the spread of electric household appliances during the 1930s. Therefore, I add county-level information on the value of per capita public works and relief spending from 1933 to 1939 as well as the per capita value of Agricultural Adjustment Administration (AAA) grants from 1933 to 1938.

An additional concern is that the estimates may in fact capture the decline of the natural ice industry between 1910 and 1925. I attempt to alleviate these concerns by adding the 30-year mean temperature for the month of January at the county level.[18] The rationale behind this approach is that the development and subsequent survival of the natural ice industry was contingent on the prevailing climatic conditions. The colder the region was, particularly during the winter months, the more competitive its natural ice industry was against the ice manufacturing industry (Anderson, 1953, p. 110).

Table 1 shows the cross-sectional variation of the main explanatory variables observed at the county level. The descriptive statistics confirm the heterogeneous diffusion of electric refrigeration, highlighting a skewed distribution with rates between 0 and 92%. The median county had a rate of electric refrigeration of about 24%. The negative mean in retail sales growth between 1929 highlights the severity of the Great Depression, which collapsed by about 45%. Per capita relief spending was quite substantial, with median per capita values

[17]The empirical strategy of this paper implements a 3DiD approach. Even if industries differ in their overall employment rates with respect to their workforce, industry fixed effects will capture level differences in employment rates.

[18]The 30-year mean temperature for the month of January refers to the period from 1901 to 1930. Source: Manson et al. (2024).

of around 207$, which represents about one fifth of a total annual median family income. AAA grants were lower in magnitude, with a median value of around 82$.

Table 1: Descriptive Statistics Macro Variables

	N	Mean	SD	Min	Median	Max
Electr. Refrigerator Ownership Rate	3095	26.83	14.93	0.00	24.20	91.80
Growth Retail Sales 1929-33	2956	-45.49	20.72	-99.92	-45.18	101.93
Public Works and Relief Spending p. C.	3041	261.34	287.34	0.27	207.80	9583.06
AAA Grants p. C.	3041	159.44	258.56	0.00	82.04	3408.13
Mean Temp. Jan. 1901-1930	3084	0.39	6.96	-17.77	0.40	19.78

As mentioned above, Figure B.3 in the Appendix provides further insights about the correlation between the share of electric refrigerators in U. S. households and the measures associated with the Great Depression. Notably, after controlling for state-specific factors, there is no systematic correlation between the growth rate of retail sales or public works and relief spending. Instead, I observe a negative association with AAA grants, which is due to the fact that refrigerator adoption correlates with urbanization.

3.4 Linked Sample of Incumbent Workers in Ice Retailing

I obtained the sample of incumbent fathers from the decennial full-count U.S. census data from IPUMS (Ruggles et al., 2024). I use data on linked individuals from Abramitzky et al. (2020), which provides links across all combinations of census waves between 1850 and 1940. Linking between census waves utilizes information on sex, age, birthplace, and name. The methodology does not require additional variables, reducing the risk of systematic correlation between the linking probability and the treatment status of individuals.[19]

My sample includes all fathers in the wholesale and retail industry (1950 industrial codes 606-699) between the ages of 18 and 60 with at least one son. They must have been in the labor force and reported an occupation in the census.[20] Again, I do not restrict individuals to those being employed. An industry-wide shock could affect the transition out of unemployment, which is also of interest.

I focus on a range of variables that capture potential labor market effects as well as alternative margins of adjustment. To measure the extensive margin, I utilize a binary indicator to determine whether incumbent workers switched their industry or occupation, became unemployed, or remained in the labor force 10 years later. Due to the lack of available income

[19]See Section A.2 in the Appendix for a brief description of the linking procedure.

[20]Based on the standard 1950 classification scheme, I include all individuals with an occupation code between 0-970.

information for historical census data, I utilize the occupation score as a proxy for the intensive margin. This score reflects the median income associated with an occupation in 1950, measured in hundreds of dollars (see Feigenbaum, 2015 and Feigenbaum and Gross, 2024 for applications). As the income measure is a crude approximation, it is necessary to consider alternative variables that may reflect different dimensions of the economic situation of individuals.[21] The occupation score does not allow for variation between industries, states, and within demographic groups based on sex, age, or race. The LIDO score by Saavedra and Twinam (2020) attempts to correct for potential within-occupational heterogeneity. However, this measure may introduce potential bias, as the predictors used to impute income may be correlated with treatment exposure. IPUMS provides further variables that reflect occupational standing, which may serve as an alternative approximation of the general income situation. Siegel (1971) classified occupations based on a survey conducted in the 1960s according to the general and social standing, deriving a consistent and common metric. Larger values indicate greater occupational prestige. Duncan (1961) proposed a measure of socioeconomic status based on income and educational attainment associated with each occupation. Again, larger values indicate higher socioeconomic status.[22] I consider these three measures in my robustness analysis.

In addition to labor market outcomes, I examine other margins of adjustment, including whether a person lived in a different county 10 years later (coded as 1 if yes, 0 if no), whether one of the residents in which the person lived owned the housing unit (1 if yes, 0 if no), and whether a person lived in a farm household (1 if yes, 0 if no). All three measures may capture different adjustments strategies. Internal mobility is a primary adaption strategy to economic shocks (Beyer and Smets, 2015). Changes in housing and living conditions may reflect deteriorating economic conditions. If a technological shock leads to a negative income shock, families may have to sell their dwelling. Moving to or starting a farm might be a way to generate income to cope with the economic situation.

Of particular interest in this study is the role of self-employment. The U.S. Census distinguishes between employees and self-employed, which I code as 1 if an individual is self-employed and 0 otherwise. In addition to the above dependent variables, I add standard socioeconomic controls to the dataset, including place of birth (state), age, race, literacy, citizenship, and marital status.[23]

[21] Another issue is that the occupation score is fixed in 1950. Thus, changes in income can only occur through corresponding changes in occupation, without allowing for within-occupation adjustment over time.

[22] Composite measures of occupational standing, such as from Siegel (1971) and Duncan (1961), have been the subject of criticism, as highlighted by IPUMS in its user note. For further information, please refer to the following `https://usa.ipums.org/usa/chapter4/sei_note.shtml` (accessed March 15, 2025).

[23] A detailed list with variable descriptions is found in Table A.3.

Table 2: Descriptive Statistics Incumbent Fathers 1930

	Ice Retailing						Other Wholesale & Retail Industries					
	N	Mean	SD	Min	Median	Max	N	Mean	SD	Min	Median	Max
Age	3890	36.51	8.02	19.00	36.00	60.00	304704	37.87	8.08	18.00	37.00	60.00
Married	3890	0.98	0.13	0.00	1.00	1.00	304704	0.99	0.11	0.00	1.00	1.00
Race	3890	0.96	0.19	0.00	1.00	1.00	304704	0.98	0.13	0.00	1.00	1.00
Literate	3890	0.95	0.21	0.00	1.00	1.00	304704	0.98	0.12	0.00	1.00	1.00
Labor Force	3890	1.00	0.00	1.00	1.00	1.00	304704	1.00	0.00	1.00	1.00	1.00
Employed	3890	0.95	0.22	0.00	1.00	1.00	304704	0.96	0.18	0.00	1.00	1.00
Self-employed	3890	0.29	0.46	0.00	0.00	1.00	304704	0.35	0.48	0.00	0.00	1.00
Foreign Born	3890	0.27	0.44	0.00	0.00	1.00	304700	0.25	0.43	0.00	0.00	1.00
Manager	3890	0.30	0.46	0.00	0.00	1.00	304704	0.41	0.49	0.00	0.00	1.00
Laborer	3890	0.12	0.33	0.00	0.00	1.00	304704	0.04	0.20	0.00	0.00	1.00
Farm	3890	0.02	0.14	0.00	0.00	1.00	304704	0.03	0.17	0.00	0.00	1.00
Dwelling	3890	0.43	0.49	0.00	0.00	1.00	304704	0.48	0.50	0.00	0.00	1.00
Occ. Score	3890	30.11	8.68	6.00	27.00	46.00	304704	31.68	9.49	3.00	29.00	80.00
PRESGL	3890	34.92	11.79	12.20	32.10	67.80	304704	39.81	11.03	0.00	37.40	81.50
SEI	3890	39.47	22.24	4.00	32.00	84.00	304704	48.22	21.35	4.00	47.00	96.00
LIDO	3710	24.32	3.94	12.27	23.07	29.47	286752	27.56	6.54	2.34	27.13	142.34

Notes: Descriptive statistics based on sample used in Table 5. The table does not include the descriptive information on migration, industry and occupation change, as these variables refer to changes in t+10.

Table 2 provides an overview of the respective sample of fathers for observations in 1930 just prior to the systematic introduction of electric refrigerators. A comparison of the ice retailing and all other wholesale and retail industries reveals several similarities across multiple dimensions. However, a few differences emerge. Specifically, the self-employment rate in ice retailing is notably lower, at 29%, compared to 35% in all other wholesale and retail industries. Furthermore, fathers in ice retailing exhibit a tendency to earn, less on average than the control group. This is consistent with a lower rate of dwelling ownership.

3.5 Outcomes for Sons of Workers in Ice Retailing

The final part of this study concentrates on the sons of fathers who worked in the wholesale and retail industry. Linking of sons between census waves again utilizes data from Abramitzky et al. (2020). My focus is on two different samples: younger sons between the ages of 6 and 9, and sons between the ages of 9 and 17. I use the younger cohort to determine if the observed erosion of the father's economic perspective affects the decision to stay in the education system or start working 10 years later, when they are between 16 and 19 years old.[24] I measure school attendance using a binary variable indicating whether sons are enrolled in any type of school or other educational institutions. For labor market participation, I use a binary measure indicating the labor force status. For the older cohort, the

[24]Labor Force status is not recorded until the age of 16.

focus is on general labor market outcomes, using similar variables as for the fathers. For the younger cohort, I do not consider additional labor market outcomes, such as employment or occupation score, because a large proportion of the sample did not end up in the labor force.

Table 3 provides an overview of the demographic characteristics of the overall sample of sons 1930.[25] A comparison of the demographics of sons of fathers working in ice retailing relative to the control group again reveals similarities. In both cases, the average age of the sons is approximately 11 years, and the majority are white. There are minor observed differences in literacy and school attendance rates, with slightly lower rates in the former. However, there are systematic differences in the labor force participation rate, which is 14 percentage points higher than in the rest of the wholesale and retail industry.

Table 3: Descriptive Statistics Sons 1930

	Ice Retailing						Other Wholesale & Retail Industries					
	N	Mean	SD	Min	Median	Max	N	Mean	SD	Min	Median	Max
Age	4596	10.71	3.43	6.00	10.00	17.00	346344	10.97	3.50	6.00	11.00	17.00
Race	4596	0.96	0.20	0.00	1.00	1.00	346344	0.98	0.14	0.00	1.00	1.00
Literate	4596	0.55	0.50	0.00	1.00	1.00	346344	0.58	0.49	0.00	1.00	1.00
Foreign Born	4596	0.03	0.17	0.00	0.00	1.00	346344	0.02	0.15	0.00	0.00	1.00
School	4596	0.88	0.32	0.00	1.00	1.00	346344	0.91	0.29	0.00	1.00	1.00
Labor Force	559	0.39	0.49	0.00	0.00	1.00	48652	0.25	0.43	0.00	0.00	1.00

Notes: Descriptive statistics are based on samples used in Tables 8 & 9. Lower numbers for labor force status occur because information is only available starting at age 16.

4 Effect of the Electric Refrigerator on Ice Retailing

To anticipate possible effects on fathers and their sons, it is crucial to understand how electric refrigeration affected the ice retailing at the aggregate level (implicit first stage). Once it becomes evident that the shock had a significant economic impact (a necessary condition), the focus shifts to incumbent fathers and their sons.

4.1 Empirical Design

The analysis utilizes a 3DiD regression model, where I compare the per capita growth rate of the fuel and ice retailing industry relative to other industries (first difference) in counties with high and low electric refrigeration adoption (second difference) over time (third difference). Therefore, I estimate the following linear industry-county level regression:

[25] A descriptive overview for all other years is in Table C.2 in Appendix C.1.

$$\%\Delta Ind^{\text{p.C.}}_{kct} = \gamma * (\Delta Refrig_c \times \text{Ice \& Fuel Ind}_k \times \text{Post } 1930_t) \qquad (1)$$
$$+ \mu_{ct} + \eta_{kts} + \kappa_{kc} + \xi_{kct}$$

where $\%\Delta Ind^{\text{p.C.}}_{kct}$ is the per capita growth rate in industry size of industry k in county c observed in year t. As discussed in Section 3.3, it is not possible to separate the fuel and ice retailing for the year 1940. Accordingly, the analysis will likely underestimate the total growth effect of the introduction of electric refrigeration will, as any change refers to a base value which also includes fuel retailing. $\Delta Refrigerator_c$ reflects the percentage of households in county c with an electric refrigerator. It serves as a proxy variable indicating the shift in refrigerator usage between 1930 and 1940. Ice & Fuel Ind_k is a binary indicator whether an industry k corresponds to the fuel and ice retailing industry. The variable Post 1930_t is a binary indicator taking the value of 1 if $t = 1940$. Parameters μ_{ct}, η_{kt}, κ_{kc} reflect county-year, state-industry-year, and industry-county fixed effects. Parameter ξ_{kct} is the residual. Coefficient γ is the main parameter of interest, reflecting the causal effect of the increase of one percentage point of households with electric refrigerators on the growth rate of fuel and ice retailing.

The 3DiD strategy offers several advantages over more simplistic regression specifications, allowing me to control for various confounding regional economic trends that might otherwise bias the estimates. For example, an alternative regression model could involve a basic shift-share DiD regression, which focuses solely on the per capita growth of fuel and ice retailing. It would merely leverage the varying rates of adoption across counties. However, this approach would neglect the fact that the adoption of electric refrigeration did not occur randomly across the United States.[26]

As discussed in Section 2, a substantial decrease in the cost of refrigerators was the driving force behind the sudden expansion, underscoring the significance of economic affordability. Therefore, I hypothesize that the local economic situation is partly reflected in the adoption rate. It is not unexpected that the adoption rate is associated with the urbanization rate of a county and other county characteristics (see Figure B.3 in the Appendix). Furthermore, the 1930s was a period marked by the onset of the Great Depression. A DiD regression may simply capture the heterogeneous economic development of counties following 1930 rather than identify the impact of the adoption of electric refrigeration.

[26] Feigenbaum and Gross (2024) uses a similar approach to analyze the impact of mechanical switching technology within the AT&T network on the employment of female telephone operators. However, they leveraged the varied timing of this technology shock across cities using a staggered DiD model. This identification strategy is not feasible in my particular context.

This limitation likely results in a degree of omitted variable bias when using a DiD approach. The regression specification in Equation 1 addresses many of the stated concerns. The inclusion of county-year fixed effects accounts for any time-varying factors at the local level, such as geographically heterogeneous economic and demographic developments. The inclusion of county-industry fixed effects allows for the possibility that certain counties, due to their time-constant geographical characteristics and endowments, are inherently suited to the development of certain industries. To control for potential latent institutional or political variables (e.g., specific industry regulations) that may vary over time and by state, I include industry-year-state fixed effects. As a result, my regression model leverages within-state variation in electric refrigeration adoption.

While controlling for a variety of potential unobserved confounding variables can facilitate the identification of a causal effect, it does not guarantee it. As with the classical DiD estimator, the 3DiD estimator requires the parallel trend assumption to hold, although it differs slightly from the classical assumption. The 3DiD estimator is de facto defined as a differential of two DiD estimators. In my case, the initial DiD estimation compares the growth rate of the fuel and ice retailing industry between high- and low-adopting counties of electric refrigeration. The second estimator performs the same calculation for the remaining industries. The estimation of the difference between the two yields the 3DiD estimate. The implicit estimation of two distinct DiD models does not necessarily imply that the parallel trend assumption must hold for both. Rather, the parallel trend assumption must be satisfied for the difference between the two. Even if both DiD estimates are biased, as long as these biases remain consistent over time, the 3DiD approach can identify a causal effect (Olden and Møen, 2022). In my case, it is probable that the growth dynamics between high- and low-adopting counties differ systematically over time. This is because urban areas may have followed a different growth path than rural areas during the period of analysis. However, if these differences in growth dynamics are uniform across industries, the 3DiD approach can filter them out. In the empirical analysis, I will provide evidence that the parallel trend assumption of the 3DiD approach likely holds.

4.2 Empirical Results

The results of Equation 1 are presented in Table 4. Column 1 provides the main estimate of interest, indicating that the distribution of electric refrigerators had a statistically significant negative impact on the per capita growth rate of fuel and ice retailing. A one percentage point increase in the use of electric refrigeration reduced the per capita growth rate by 2.3 percentage points. As documented in Miller (1960), the proportion of U.S. households with electric refrigerators increased from 8.8% to 45.8% between 1930 and 1940. This represents a reduction in the growth rate of approximately 85.1% percentage points.[27] In 1930, the average per capita industry growth rate of fuel and ice retailing was approximately 51%. Thus, there was a clear association between the shock and a decline in economic importance in per capita terms. It should be noted that these calculations are lower-bound estimates, as the base value includes individuals from the fuel industry. Therefore, the negative impact on the ice retailing would probably have been significantly greater. The increased demand due to population growth may have partially offset the negative impacts of electric refrigeration on growth in per capita terms. However, Column 1 of Table C.3 in the Appendix also provides negative estimates for the growth rate of absolute industry size.[28]

Table 4 – Implicit First Stage: Aggregated per Capita Growth Effects Ice & Fuel

	%ΔInd p.C.				
	(1)	(2)	(3)	(4)	(5)
$\Delta Refrig \times$ Ice & Fuel Ind. × Post 1930	-0.023***	-0.023***	-0.023***	-0.021***	
	(0.005)	(0.006)	(0.005)	(0.005)	
$\%\Delta Retail \times$ Ice & Fuel Ind. × Post 1930		0.004			
		(0.004)			
Relief Spending × Ice & Fuel Ind. × Post 1930		0.010			
		(0.147)			
AAA Grants × Ice & Fuel Ind. × Post 1930		0.053			
		(0.058)			
Avg. Temp. Jan. × Ice & Fuel Ind. × Post 1930			-0.049		
			(0.033)		
Refrig^G × Ice & Fuel Ind. × Post 1930					-0.168***
					(0.028)
Mean Y (Ice & Fuel Ind. 1930)	0.511	0.511	0.511	0.511	0.511
County-Year FE	Yes	Yes	Yes	Yes	Yes
County-Industry FE	Yes	Yes	Yes	Yes	Yes
State-Industry-Year FE	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.31386	0.32009	0.31369	0.30139	0.31387
Observations	797,875	768,940	795,634	657,883	797,875

Notes: The dependent variable is the per capita industry growth rate for all columns. Column 1 corresponds to the main estimation, and Column 2 controls for further variables related to the Great Depression, including the growth rate in retail sales between 1929 and 1933 as a proxy for the severity of the crisis, public work and relief spending per capita, and AAA grants per capita. Column 3 incorporates the 30-year mean temperature for the month of January at the county level, while Column 4 removes all observations from states that did not have an ice manufacturing industry in 1900. Column 5 employs a transformation of the main variable, $\Delta Refrig_c$, by reflecting the decile, ranging from 1 to 10. Standard errors are clustered at the industry-county level and reported in parentheses. The specified mean value reflects the average county growth rate of the ice & fuel industry between 1920 and 1930 in per capita terms. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

[27] This calculation is based on $37 \times 0.023 \times 100 = 85.1\%$.

[28] In economic terms, the adoption of electric refrigeration clearly led to economic stagnation or even partial destruction of the industry. The refrigeration shock reduced the growth rate on average by $37 \times 0.018 \times 100 = 66.1\%$, while the average growth rate in 1930 was around 66%.

Robustness: I conduct several robustness checks to ensure that the results represent a lower bound estimate. A significant concern is the differential impact of the Great Depression on different industries in different locations. Thus, I include the growth rate in retail sales between 1929 and 1933 as a proxy for the severity of the crises. It is interacted in the same manner as the adoption rate in electric refrigeration. This approach permits for estimating the potential impact of the Great Depression on fuel and ice retailing. Similarly, I include an interaction term for public work and relief spending per capita as well as AAA grants per capita, which were designed to mitigate the consequences of the Great Depression. The inclusion of these variables has no effect on the main parameter of interest, as is evident in Column 2 of Table 4.[29]

An additional concern is that the estimates may in fact capture the decline of the natural ice industry between 1910 and 1925. I attempt to alleviate these concerns in two ways: First, I add the 30-year mean temperature for the month of January at the county level (Column 3). Second, I exclude all U.S. states that, according to Hunt (1902), did not have a manufacturing ice industry in 1900, but rather only a natural ice industry. Accordingly, the natural ice industry should play a less prominent role in my sample of analysis (Column 4). Neither adjustment affects the main conclusion.

In addition, Column 5 focuses on the definition of the treatment variable. This column presents the results by transforming the variable $\Delta Refrig_c$ into an ordinal variable, dividing it into its deciles. The results remain robust to a variable transformation. Lastly, Figure B.4 in the Appendix displays the results of the corresponding event-study coefficients of Equation 1. The two figures demonstrate that a statistically significant trend did not occur prior to 1930, providing evidence that the parallel trend assumption is reasonable to hold.[30]

The results provide clear evidence that the introduction of electric refrigeration across U.S. households constituted a significant threat for the ice retailing industry. Given the unfavorable outlook for the ice retailing industry, the next section assesses how those affected by this technological shock generally adapted to the worsened labor market prospects.

[29] Public work and relief spending per capita is transformed using the natural logarithm. AAA grants per capita are transformed by the inverse hyperbolic sine function due to occurring zeros.

[30] As mentioned previously, the 3DiD approach estimates the differential between two DiD estimates. Figure B.5 in the Appendix displays the idea behind this. The two event studies examine the growth rates of fuel and ice retailing and all other industries separately. They compare high- and low-adopting counties before and after 1930. The data reveals a clear pattern: in counties with high levels of adoption, the overall rate of industry growth in 1900 was consistently higher relative to low-adopting counties. However, the 3DiD approach can control for this bias, provided that the differential between the two simpler DiD models remains constant. As illustrated in Figure B.5, the point estimates and confidence intervals exhibit consistent overlap in all periods prior to 1930, providing no evidence that the differential changes over time.

5 Effect on Incumbent Ice Dealer

The subsequent empirical analysis focuses on incumbent fathers using a sample of individuals from linked census waves between 1900 and 1940.[31] I compare individuals in year t to their respective outcomes 10 years later, as done in Feigenbaum and Gross (2024). I again leverage a 3DiD model by comparing individuals engaged in ice retailing with those in other industries of wholesale and retail trade (first difference) in counties with high and low rates of adoption of electric refrigeration (second difference) over time (third difference).

5.1 Empirical Strategy Incumbent Fathers

To determine the causal effect of the widespread adoption of electric refrigerators on workers in the retail ice industry, I specify the following linear regression model:

$$\begin{aligned} Y_{ict}^{t+10} = \beta{*}(\Delta Refrig_c \times \text{Ice Ind}_{it} \times \text{Post 1920}_t) \\ + \theta' X_{it} + \gamma_{ct} + \rho_{kts} + \psi_{ck} + \epsilon_{ict} \end{aligned} \quad (2)$$

with Y_{ict}^{t+10} as the respective outcome variable 10 years later for a father i who resided in county c during census year t. The binary variable Ice Ind_{it} indicates whether a person worked in the ice retailing industry in census year t. $\Delta Refrigerator_c$ again corresponds to the percentage of households in county c with an electric refrigerator in 1940. The variable Post 1920_t is a binary indicator taking the value of 1 if $t = 1930$. It is important to note that the post dummy shifts to $t = 1920$ in comparison to Equation 1, as the regression model now relates to future outcomes 10 years after. The main parameter of interest is then given by β and identifies the causal effect of mechanical refrigeration diffusion on outcomes Y_{ict}^{t+10}. X_{it} are individual-level controls and γ_{ct}, ρ_{kts} and ψ_{ck} are county-year, state-industry-year, and industry-county fixed effects.[32] Parameter ϵ_{ict} is the residual. Standard errors are clustered at the industry-county level.

The 3DiD model in this section is comparable in structure to Equation 1 and therefore shares the same identifying assumptions. However, there are some differences between the two models. In contrast to the previous regression model, the set of industries under consideration is limited to those within the wholesale and retail industry. As the focus is now on individuals, it is important to include a proper control group relative to individuals from

[31] In fact, it is a repeated cross-section of linked individuals across census waves.

[32] Individual-level controls include a dummy for literacy and information on age group, citizenship status, race, marital status, and place of birth.

the ice retailing industry. Those employed in sectors such as mining, agriculture, or manufacturing may differ significantly from those engaged in retailing in educational or family backgrounds as well as their living and working conditions. Although the 3DiD regression controls for various potential confounding factors, focusing on a more similar control group in terms of background and work environments should further reduce the potential for omitted variable bias. Furthermore, the analysis consists of repeated cross sections of incumbent fathers and their outcomes 10 years later. This raises concerns that changes in the sample composition across years may influence the results. As demonstrated in the robustness analysis, I re-run the estimation with a balanced panel dataset of incumbent fathers over three waves, demonstrating that the composition of the sample is not a concern in this study.

5.2 Empirical Results Incumbent Fathers

Table 5 presents the regression results for the six main labor market outcomes of incumbent fathers in the ice retailing industry. The decline of ice retailing in the U.S. resulted in an increased probability of incumbent fathers leaving the industry. A one percentage point increase in electric refrigeration adoption corresponds to an increased probability of industry switching of about 0.29 percentage points (Column 1). Putting this into perceptive, as in Section 4, the increase in electric refrigerator ownership in the U.S. by approximately 37 percentage points increased the probability of leaving the industry by 11 percentage points. In 1920, before the refrigerator shock, an average of 70% of fathers working in ice retailing left the industry 10 years later. The technological shock resulted in a further substantial increase relative to the mean of approximately 15%. The increased likelihood of not remaining in the same industry 10 years later also appears to have increased the likelihood of not working in the same occupation 10 years later (Column 2) by 0.21 percentage points. It further resulted in a reduction in occupational earnings (Column 3) by 0.33 percent for a one percentage point increase in electric refrigeration ownership. Again, given an average increase in electric refrigerator ownership of 37 percentage points, the semi-elasticities in the income regression suggest a reduction in income of 12%.[33]

In contrast, I did not observe an effect on average on the probability of being employed or being in the labor force, nor does it influence the probability of being self-employed.

[33] Given that the average income of ice retailers is greater than 10 in hundreds of dollars (see Table 2), I approximate the semi-elasticities by the corresponding logarithmic interpretation (Bellemare and Wichman, 2020). Thus I obtain the effect by calculating $100 \times -0.0033 \times 37 = -12.21\%$.

Table 5 – Labor Market Effects

	$\Delta Industry$ (1)	$\Delta Occupation$ (2)	asinh Occup. Score (3)	Employed (4)	Labor Force (5)	Self-Employed (6)
$\Delta Refrig \times$ Ice Ind. $\times$ Post 1920	0.0029***	0.0021**	-0.0033***	-0.0005	-0.0004	0.0004
	(0.0011)	(0.0010)	(0.0012)	(0.0007)	(0.0003)	(0.0012)
Mean Y (Ice Industry 1920)	0.6955	0.7424	3.9486	0.9208	0.9984	0.2729
Year-County FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry-Year-State FE	Yes	Yes	Yes	Yes	Yes	Yes
County-Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Literate FE	Yes	Yes	Yes	Yes	Yes	Yes
Age Bin FE	Yes	Yes	Yes	Yes	Yes	Yes
Citizen FE	Yes	Yes	Yes	Yes	Yes	Yes
Race FE	Yes	Yes	Yes	Yes	Yes	Yes
Married FE	Yes	Yes	Yes	Yes	Yes	Yes
Birthplace FE	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.15434	0.09962	0.11796	0.07941	0.07558	0.15222
Observations	814,308	814,308	814,308	627,497	814,308	814,308

Notes: The dependent variables in Columns 1, 2, and 4-6 are binary. Column 1 indicates whether a father switched industries, and Column 2 indicates whether he switched occupations (yes = 1). Column 3 takes the inverse hyperbolic sine transformation of the occupation score as an approximation to the logarithm due to the occurrence of zero values. Column 4 focuses on whether a father continues to have employment (yes = 1). Similarly, Columns 5 and 6 focus on the labor force and self-employment status, respectively. Observations in Column 4 are lower due to the absence of employment information in 1920. Standard errors are clustered at the industry-county level and reported in parentheses. The specified mean value reflects the average of the dependent variables of fathers in the ice retailing industry observed in 1920.* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Further Margins of Adjustment: In addition to the adverse labor market implications for incumbent fathers in the ice retailing industry, alternative margins for adjustment appear to be of limited significance. Table 6 presents the results of the probability of residing in a different county (Column 1), owning a dwelling (Columns 2), or living on a farm (Column 3). No statistically significant results can be observed for any of the variables, which is particularly noteworthy in the context of the internal migration result. Internal mobility is often a primary adaption strategy to economic shocks (Beyer and Smets, 2015). In this case, the negative income shock for incumbent fathers did not appear to be substantial enough to motivate, force, or hinder them to change their county of residence 10 years later. This finding is consistent with historical case studies that find no geographic movement across counties or states following a major technology shock in the U.S. (Cockriel, 2023; French, 2022).

Table 6 – Further Margins of Adjustment

	Migration (1)	House (2)	Farm (3)
$\Delta Refrig \times$ Ice Ind. $\times$ Post 1920	-0.0003	-0.0004	0.0000
	(0.0013)	(0.0013)	(0.0008)
Mean Y (Ice Industry 1920)	0.3367	0.5669	0.0922
Year-County FE	Yes	Yes	Yes
Industry-Year-State FE	Yes	Yes	Yes
County-Industry FE	Yes	Yes	Yes
Literate FE	Yes	Yes	Yes
Age Bin FE	Yes	Yes	Yes
Citizen FE	Yes	Yes	Yes
Race FE	Yes	Yes	Yes
Married FE	Yes	Yes	Yes
Birthplace FE	Yes	Yes	Yes
R^2	0.13586	0.15887	0.20168
Observations	814,308	814,308	814,308

Notes: The dependent variables in Columns 1-3 are binary in nature. Column 1 indicates whether a father resides in a different county than previously (yes = 1). Column 2 indicates whether the household owns the dwelling in which they are living (yes = 1). Column 3 indicates whether the household lives on a farm (yes = 1). Standard errors are clustered at the industry-county level and reported in parentheses. The specified mean value reflects the average of the dependent variables of fathers in the ice retailing industry observed in 1920.* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Comparing Effects: This section assesses how these results align with other studies that have analyzed the labor market impacts of technological shocks in a historical context. Cockriel (2023) focuses on the de-skilling of shoemakers resulting from the introduction of the McKay stitcher, a sewing machine for shoe soles. The author estimated that a one standard deviation increase in exposure to the technological effects of the McKay stitcher increased the probability of occupational change by 7.6 percentage points for traditional shoemakers. In contrast, French (2022) concentrates on the mechanization of the agricultural sector in the early 20th century. In this instance, a one standard deviation increase in technological adoption corresponded to an increase in occupational switching for workers in agriculture of approximately 3.7 percentage points. Estimates for fathers in the ice retailing industry suggest that a one standard deviation increase in the use of electric refrigeration increased the probability of occupational switching by about 3.15 percentage points.[34] Although this result is smaller than two previous studies, they are not systematically different in their absolute magnitude. Regardless of the type of technological shock, none of the studies have identified statistically significant instances of incumbents coping with the shock by migrating. Any labor market adjustments appear to occur on a local scale.[35]

Robustness: The results are robust with respect to various specifications. For example, the results remain consistent when employing alternative measures of the dependent variables. Table C.4 presents the results with three alternative income and occupational standing measures. The results are all consistently negative. The data reveals that fathers employed in the ice retailing industry during the 1930s experienced adverse effects in income, prestige, and socioeconomic status. Furthermore, excluding individual-level controls from the regression model does not alter the main conclusion (see Table C.5 in the Appendix). The baseline regression includes all fathers within labor force, regardless of employment status. However, conditioning on employment amplifies the estimated effects (see Table C.6 in the Appendix).

Table C.7 addresses potential concerns regarding the influence of sample compositions across census years on the results. I construct a linked panel data set for the period 1920 to 1940 based on the 1930 sample of incumbent fathers aged 30 to 50. The results remain robust to a balanced panel regression.

As previously discussed, the results may be subject to further concerns regarding the identification of the causal effect. First, the specific parallel trend assumption for a 3DiD model must hold. Figures B.6 and B.7 display the corresponding event study graph for the various outcomes. In all cases, there is no statistically significant pre-trend. Statistically insignificant pre-trends also alleviate concerns that part of the shock may have already occurred in the 1920s or that forward-looking agents may have adjusted in advance.

The probability of linking individuals across census waves is not random and directly correlates with certain person characteristics. In addition, representatives of a linked sample may not be available (Bailey et al., 2020).[36] In my case, I use information about age, state of birth, and full name for linking, each of which potentially correlates with variables also related to the treatment exposure. For example, linking individuals with an immigration

[34] One standard deviation for electric refrigeration adoption is approximately 15%. Thus, the values are obtained by calculating $100 \times (15 \times 0.0021)$.

[35] Feigenbaum and Gross (2024) and Ager et al. (2023) focus on women and are therefore not directly comparable.

[36] Bailey et al. (2020) evaluates the performance of various historical linking procedures for the United States and concludes that neither manual linking by persons or automated linking produces representative samples.

background is often more difficult than native individuals. Spelling errors by the census enumerator due to less common names as well as return migration may also contribute to difficulties in identifying the same person in two different census waves (Abramitzky et al., 2021).

In line with recommendations from Bailey et al. (2020), I re-run the main specification using inverse probability weights (IPW) to address selective linking and non-representative samples.[37] Replicating the main estimation results using inverse probability weights does not alter the results (see Table C.8). Furthermore, I assess the ability of my 3DiD regression model to explain linking probability in accordance with Equation 2. I subsequently define the dependent variable as a binary indicator of linking status. The regression results do not provide evidence that the treatment exposure predicts the linking probability (see Table C.9). Overall, the empirical regression results are robust to various specifications and tests, indicating that the introduction of electric refrigeration significantly impacted the labor market for incumbent fathers in the ice retailing industry.

5.3 Heterogeneity

Age: The results from Table 5 might face the risk of masking substantial effect heterogeneity. Since the focus is not only on incumbent fathers, but also on their sons, it is valuable to assess the differential effect of the widespread adoption of electric refrigeration on younger fathers with typically younger sons. Fathers may adjust differently depending on the age of their children, resulting in heterogeneous labor market responses. Younger fathers may also differ systematically in their set of skills, experience, or other unobserved characteristics, which may simultaneously lead to different labor market outcomes for themselves and their sons.

Table 7 divides the sample into fathers equal to or younger than 40 years old and those older than 40. The younger age cohort of fathers represented the majority of the main effects. For example, a 37 percentage point increase in electric refrigerator ownership corresponds to a 16 percentage point increase in the probability of a father leaving the ice retailing industry 10 years later. Similarly, the probability of occupational change increases by 11 percentage points and wages decrease by about 14% for this age group. Interestingly, the older age cohort responds to the technological shock by leaving the labor force, corresponding to a 5 percentage point decline in the participation rate. Thus, young fathers experienced a greater degree of burden due to the technological change.

[37]For information on how to calculate IPWs, see section A.3 in the Appendix.

Table 7 – Labor Market Outcomes by Age Cohort

	$\Delta Industry$		$\Delta Occupation$		asinh Occup. Score		Employed		Labor Force		Self-Employed	
	Age < 41	Age ≥ 41	Age < 41	Age ≥ 41	Age < 41	Age ≥ 41	Age < 41	Age ≥ 41	Age < 41	Age ≥ 41	Age < 41	Age ≥ 41
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
$\Delta Refrig \times$ Ice Ind. $\times$ Post 1920	0.0043***	-0.0008	0.0031**	0.0023	-0.0040**	-0.0047	-0.0003	-0.0023	0.0000	-0.0014**	0.0002	-0.0023
	(0.0013)	(0.0025)	(0.0013)	(0.0027)	(0.0016)	(0.0035)	(0.0009)	(0.0021)	(0.0003)	(0.0006)	(0.0015)	(0.0028)
Year-County FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry-Year-State FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
County-Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Literate FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Age Bin FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Citizen FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Race FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Married FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Birthplace FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.17686	0.21655	0.12667	0.16947	0.15735	0.18850	0.10672	0.14582	0.09823	0.13794	0.17976	0.21498
Observations	513,310	300,998	513,310	300,998	513,310	300,998	398,590	228,907	513,310	300,998	513,310	300,998

Notes: Columns 1-12 include the same variables and sample as Table 5. The sample is split along the age of 41. Standard errors are clustered at the industry-county level and reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Self-Employment: The prospect of the American Dream that anyone can go from rags to riches, is closely linked to the country's entrepreneurial spirit. As such, self-employment and entrepreneurship are frequently regarded pathways to social mobility, particularly for social groups encountering challenges in conventional wage labor markets (Glazer and Moynihan, 1970).[38] In addition, entrepreneurship and self-employment can act as coping strategies to mitigate negative economic shocks such as layoffs. Several studies have found that unemployment and challenging economic conditions increase the likelihood of individuals starting their own business (Babina, 2019; Gautam, 2023; von Greiff, 2009; Hacamo and Kleiner, 2022; Røed and Skogstrøm, 2014). However, less is known about the impact of a technological shock on individuals' decisions to continue with their own business and the types of adaptation measures taken.[39]

Figure 4 presents the findings from regression analyses that split the sample according to self-employment status. These results unveil interesting heterogeneity among incumbents regarding their labor market adjustments. In general, self-employed fathers adjusted within the ice retailing industry or left it entirely, while dependent employees sought opportunities outside of the ice retailing industry. More specifically, a one percentage point increase in electric refrigeration increased the probability of leaving the ice retailing industry by 0.37 percentage points for dependent employees (see Table C.10 in the Appendix for the numeric values). In contrast, self-employed fathers faced a reduced probability of maintaining their

[38] This is especially the case in the wholesale and retail industry, where 36% of all self-employed individuals in 1930 were born outside the United States. Borjas (1986) observes a higher rate of self-employment among immigrants compared to natives during the 1970s and 1980s. Similarly, Yuengert (1989) emphasizes the significance of self-employment as a means of integration for male immigrants.

[39] Dillon and Stanton (2017) provides a semi-structural model that models the general decision to enter and exit self-employment. However, the role of a technological shock is not explicitly considered.

own business and a tendency to drop out of the labor force, though the latter effect is not statistically significant at the 10% level (p-value ~ 0.13).[40] The negative consequences for self-employed fathers resulted in a higher probability of finding employment 10 years later. However, an increased probability to switch occupations also accompanies these labor market adjustments, although again this is a borderline case and is not statistically significant at the 10% level. The associated point estimates for the occupation score suggest a downgrading in occupational status, which led to a reduction in income. A similar pattern for occupational switching and impacts on the occupation score is evident for dependent employees.

Although it is challenging to derive the exact mechanisms behind the adjustment process from the available data, the results suggest an association between self-employment status and certain industry-specific knowledge and skills that allow them to adjust within the industry. These may include knowledge of distribution networks, industry practices, or general business practices. For example, self-employed fathers in ice retailing had a higher occupation score on average and often took management roles within their company, while dependent employees occupied often simpler jobs.[41] However, the point estimates suggest that the within-industry adjustment came at a significant price. While in 1930, 74% of self-employed ice retailers reported a management related occupation, only 34% continued to do so 10 year later. Thus, it is not surprising that the associated employment probability increased for this group, potentially compensating for the occupational downgrading.

[40] The negative effect on self-employment remains when conditioning on labor force participation 10 years later. Thus, dropping out of self-employment is not due to leaving the labor force (see Table C.11).

[41] In 1930, the mean occupation score for self-employed fathers in ice retailing was 37.4, while dependent employees had a value of 27.1.

Figure 4 – Labor Market Effects by Self-Employment Status

Notes: **Estimated coefficients** and [90% & 95%] **confidence bands**. Standard errors are clustered at the industry-county level. Corresponding results are listed in Table C.10.

6 Intergenerational Consequences of a Technological Shock

To answer questions about intergenerational effects, I distinguish between two samples. The first sample focuses on sons between the ages of 6 and 9 and their outcomes 10 years later. Thus, my goal is to disentangle the tradeoff between school attendance and labor force participation for those between 16 and 19 years old. The second sample includes all males between the ages of 9 and 17, providing insight into the different intergenerational labor market consequences 10 years later. Therefore, I observe the results for the older cohorts between the ages of 19 and 27.

6.1 Empirical Strategy Sons

Equation 3 refers to the linear regression model analyzing the outcomes of the sons and has the same functional form as for the fathers. Therefore, Y_{ict}^{t+10} reflects the outcome observed in $t + 10$ years for individual i of census wave t living in county c.[42] I control for individual characteristics of the sons via X_{it}^{Son} and add controls for their fathers X_{it}^{Father}. As done previously, I add several fixed effects corresponding to the father, more specifically county-year (γ_{ct}^{Father}), state-industry-year (ρ_{kts}^{Father}), and county-industry (ψ_{ck}^{Father}). The primary interest lies in the estimation of β, which captures the causal relationship between the distribution of electric refrigerators and the outcomes of the sons of ice dealers.

$$\begin{aligned} Y_{ict}^{t+1} = \beta * (\Delta Refrig_c \times \text{Ice Ind}_{it} \times \text{Post 1920}_t) \\ + \theta' X_{it}^{Son} + \Theta' X_{it}^{Father} + \gamma_{ct}^{Father} + \rho_{kts}^{Father} + \psi_{ck}^{Father} + \epsilon_{ict} \end{aligned} \tag{3}$$

Effect on Young Cohort: Given the negative consequences for incumbent ice retailers, the question arises as to whether such an impact might have spilled over to their children. A job displacing technological shock could have an impact for the following reasons. Unemployment or loss of income might reduce the ability of parents to invest in their child's human capital (Hilger, 2016; Mörk et al., 2020). In addition, financial constraints at home may force working-age sons to leave school earlier than expected and contribute to the household income. A labor market shock can also influence the opportunity cost of going to school, as the worsening labor market conditions in the ice retail industry offered less attractive economic opportunities. This may result in higher school attendance rates (Saad and Fallah,

[42] I only consider sons who live together with their fathers in the same household, thus the same county.

2020; Shah and Steinberg, 2017).

As demonstrated in Table 8, a tradeoff between schooling and labor force participation is evident among the young cohort. A one percentage point increase in the electric refrigeration ownership rate decreased the probability of staying in school by 0.5 percentage points 10 years later. Given that the average share of households with an electric refrigerator increased by about 37 percentage points, it can be extrapolated that the probability of school attendance decreased by about 19.6 percentage points for the treatment group. This decline is economically significant. Prior to the shock, an average of 36% of all young sons of ice retailers were still in school 10 years later. The impact on the labor force participation rate is inversely related, although the coefficient is with 0.33 percentage points smaller in magnitude, indicating that some sons do not attend educational institutions or enter the labor market.[43]

Table 8 – School Attendance and Labor Force Participation of the Young Cohort

	Attending School (1)	Labor Force (2)
$\Delta Refrig\times$ Ice Ind. Father $\times$ Post 1920	-0.0050***	0.0033*
	(0.0018)	(0.0019)
Mean Y (Ice Industry 1930)	0.3593	0.5940
Year-County Father FE	Yes	Yes
Industry Father-Year-State Father FE	Yes	Yes
County Father-Industry Father FE	Yes	Yes
Literate Father FE	Yes	Yes
Age Bin Father FE	Yes	Yes
Citizen Father FE	Yes	Yes
Race Father FE	Yes	Yes
Married Father FE	Yes	Yes
Birthplace Father FE	Yes	Yes
Literate FE	Yes	Yes
R^2	0.18865	0.19154
Observations	427,551	427,551

Notes: Both dependent variables are binary. Column 1 indicates whether a son is still in school (yes = 1), and column 2 indicates whether a son is in the labor force (yes = 1). Standard errors are clustered at the industry-county level of the father and are reported in parentheses. The reported mean reflects the average of the dependent variables for sons whose fathers are in the ice retail industry observed in 1920.* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

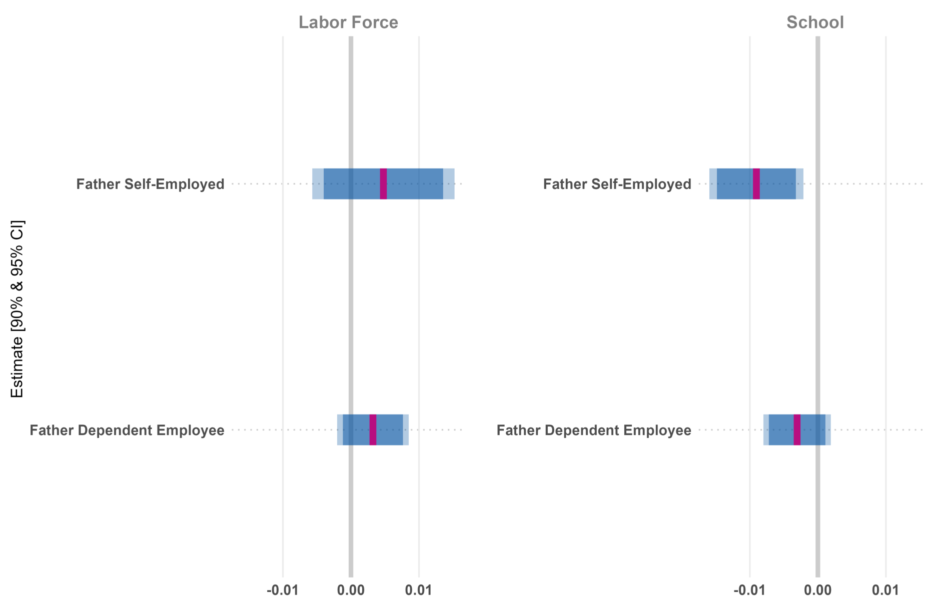
What is the impact of fathers' self-employment status on the trade-off between school and the labor market? The point estimates in Figure 5 suggest that both groups of sons

[43] The findings concerning school attendance for the young cohort are robust across multiple specifications. Specifically, the results hold when using inverse probability weights (see Table C.13). The estimates regarding the labor force participation are less robust in terms of statistical significance. However, the point estimates demonstrate the same direction and are of similar magnitude. Moreover, event study estimates indicate no violation of the parallel trend assumption within a 3DiD framework (see Figure B.8).

exhibit a tendency to leave school to enter the labor market. This finding is not unexpected, as economic adjustment is evident among both groups of fathers following the introduction of electric refrigerators. However, the results indicate a clear statistically significant relationship with respect to school attendance only for sons of self-employed fathers.

The observed effects for the self-employed are not the result of sons being substitutes for other employees in the family business. Table C.15 distinguishes between fathers who remained self-employed and those who did not. Column 2 of Table C.15 shows that the coefficient does not change by considering only fathers who left self-employment. It strengthens the argument that declining school attendance rates are due to constrained economic conditions at home.[44]

Figure 5 – Effect on Young Cohort by Birthplace and Self-Employment Status of Father



Notes: **Estimated coefficients** and [90% & 95%] **confidence bands**. Standard errors are clustered at the county-industry level of the father. Corresponding results are listed in Table C.14.

Effect on Older Cohort: The second analysis focuses on sons aged 10 and older, the majority of whom were already part of the labor force 10 years later. The introduction of electric refrigeration also may have impacted the career choice of older sons. The observation that the skills of one's own father are no longer needed may lead to a decoupling of following the same career path, systematically choosing other occupations or industries (Cockriel, 2023). It may also affect risk preferences, influencing the choice of following a father into

[44] French (2022) and Cockriel (2023) also find negative effects on educational outcomes for sons of displaced workers. However, a study by Aizer et al. (2025) reveals a slightly higher number of schooling years for the sons of fathers who lost their jobs due to Prohibition in 1919.

self-employment. If risk aversion increased after the shock, sons might not try the riskier path of self-employment (Shigeoka, 2019).

It is a priori ambiguous whether a decoupling of a career path takes place and whether it leads to a better or worse economic situation. Following one's father's occupation could lead to an inefficient allocation of labor (Lo Bello and Morchio, 2022). However, occupational persistence is also evident among certain high-wage occupations (Mocetti, 2016; Raitano and Vona, 2021). Thus, a shock that decouples occupational persistence might be beneficial for the former group in terms of labor outcomes, but harmful for the latter. The consequences can be particularly negative if the sons of self-employed fathers miss out on the opportunity to inherit the family business or see a decline in the value of the industry-specific knowledge passed on by their parents (Hvide and Oyer, 2017; Holtz-Eakin et al., 1994).

Contrary to school outcome, the older cohorts were not substantially affected by the consequences of the introduction of electric refrigerators. Table 9 presents the results, providing precisely estimated null effects along several labor market outcomes. The analysis does not demonstrate a systematic influence on labor force participation, employment probability, or income, as measured by occupation score. Additionally, the shock did not discourage the decision to be self-employed or follow their fathers into the wholesale and retail industry.[45] Furthermore, distinguishing by the self-employment status of the father does not indicate a systematic pattern on affected sons (see Figure 6).

[45] The corresponding event study does not indicate a systematic violation of the parallel trend assumption (see Figure B.9). In terms of labor income, alternative measures, such as the LIDO score, demonstrate similar insights (Table C.17 in the Appendix.). The application of inverse probability weights still yields precisely estimated null results (Table C.18 in the Appendix). The same holds true if I condition on being in employment (Table C.19 in the Appendix).

Table 9 – Labor Market Effects Sons Older Cohort

	Labor Force (1)	Employed (2)	asinh Occup. Score (3)	Self-Employed (4)	Wholesale & Retail (5)
$\Delta Refrig\times$ Ice Ind. Father $\times$ Post 1920	0.0004	-0.0002	0.0001	-0.0009	-0.0002
	(0.0010)	(0.0013)	(0.0012)	(0.0010)	(0.0016)
Mean Y (Ice Industry 1930)	0.9423	0.8934	3.8767	0.0763	0.2689
Year-County Father FE	Yes	Yes	Yes	Yes	Yes
Industry Father-Year-State Father FE	Yes	Yes	Yes	Yes	Yes
County Father-Industry Father FE	Yes	Yes	Yes	Yes	Yes
Literate Father FE	Yes	Yes	Yes	Yes	Yes
Age Bin Father FE	Yes	Yes	Yes	Yes	Yes
Citizen Father FE	Yes	Yes	Yes	Yes	Yes
Race Father FE	Yes	Yes	Yes	Yes	Yes
Married Father FE	Yes	Yes	Yes	Yes	Yes
Birthplace Father FE	Yes	Yes	Yes	Yes	Yes
Literate FE	Yes	Yes	Yes	Yes	Yes
R^2	0.10263	0.10968	0.17988	0.15026	0.12609
Observations	567,531	405,781	523,370	523,370	523,370

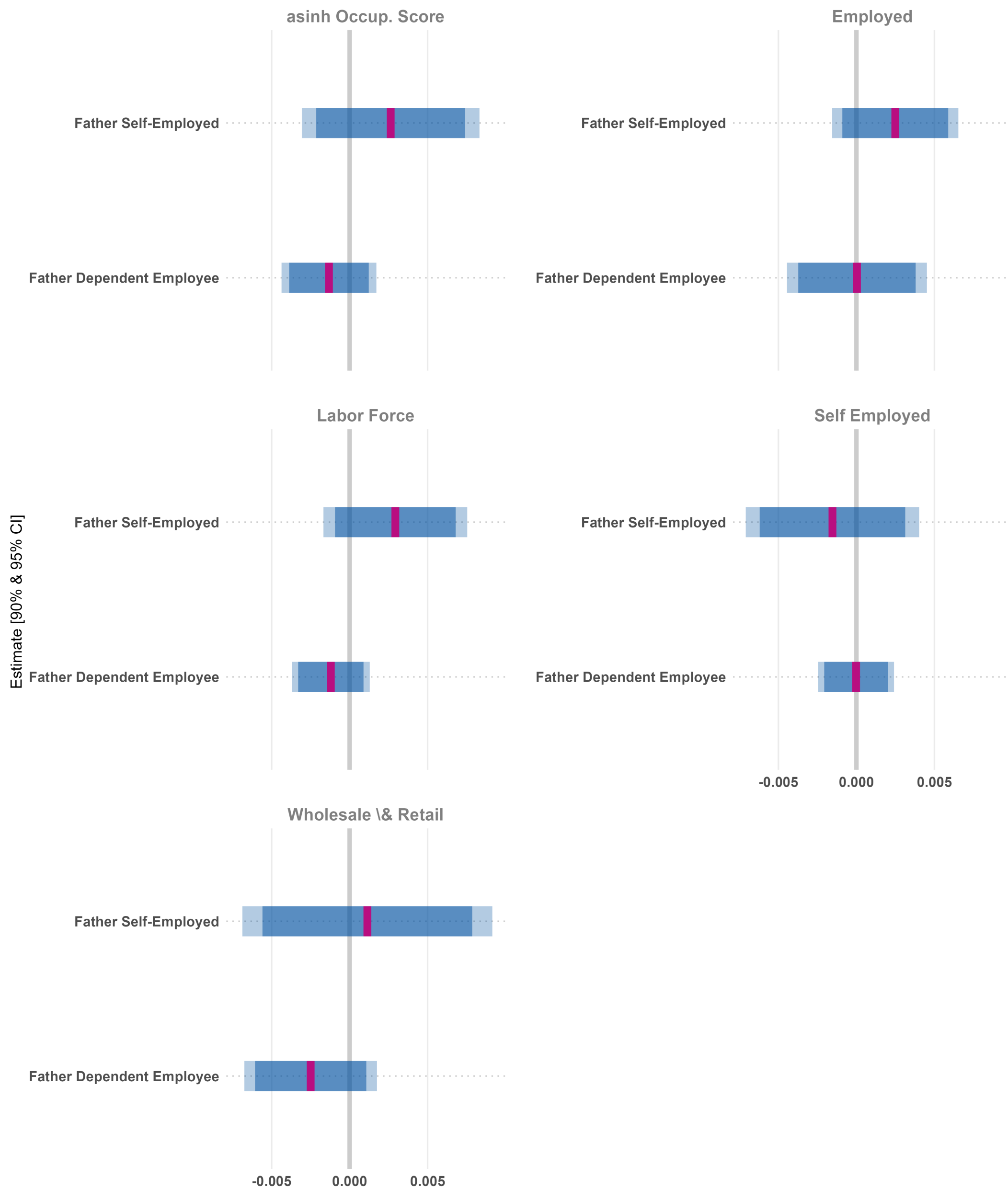
Notes: The dependent variables in Columns 1, 2, 4, and 5 are binary. Columns 1 and 2 indicate whether a son is in the labor force (yes = 1) and whether he is employed (yes =1). Column 3 takes the inverse hyperbolic sine transformation of the occupation score as an approximation to the logarithm due to the occurrence of zero values. Column 4 indicates whether a son is self-employed, and Column 5 indicates whether a son works in the wholesale and retail industry. Observations in Column 2 are lower due to the absence of employment information in 1920. Standard errors are clustered at the industry-county level of the father and reported in parentheses. The reported mean reflects the average of the dependent variables for sons of fathers employed in the retail ice industry observed in 1920. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Limitations: The findings of this study indicate that intergenerational spillover effects of technological shock, particularly among younger cohorts. However, the analysis is subject to certain limitations. First, the focus on school attendance does not provide evidence regarding the quality of the educational level. Second, observed labor market outcomes are relative to the beginning of one's working life, with a maximum age of 27 years, which cannot fully capture the potential consequences on the level of permanent earnings. Related estimates are often prone to overestimating potential income mobility (Deutscher and Mazumder, 2023; Feigenbaum, 2015). The role of age also relates to the decision to start a business, which most people make later in life. For example, in 1930, only 10 percent of self-employed individuals in the wholesale and retail industry were below the age of 28.[46] Thus, the current estimates may not fully capture the extent of the impact on future self-employment. One potential solution is to consider the 1950 U.S. census for further estimations, for which a preliminary version has been made available (Ruggles et al., 2024). Doing so will not only enable the capture of more appropriate long-term consequences of reduced school attendance, but also provide a more accurate representation of permanent income effects and self-employment participation. Moreover, it will offer a more comprehensive analysis of the dissolution of the ice retailing industry. Thus far, linkages for the 1950 census are not available by Abramitzky

[46] This refers to all individuals, irrespective of whether they have a son. Author's calculation based on the full Count Census of Population (Ruggles et al., 2024).

et al. (2020), not allowing an extension within the current empirical framework.[47]

Figure 6 – Effect on Older Cohort by Self-Employment Status of Father



Notes: **Estimated coefficients** and [90% & 95%] **confidence bands**. Standard errors are clustered at the county-industry level of the father. Corresponding results are listed in Table C.16.

[47]Ruggles et al. (2024) already provided preliminary linkages for the 1950 census based on a probabilistic approach (see Helgertz et al. (2022) for a description). However, they utilize a multitude of control variables in addition to age, birthplace, and names that may correlate with the treatment exposure and thus introduce bias into the results. In contrast, the approach by Abramitzky et al. (2020) is more conservative, typically leading to a lower successful linkage rate across census waves.

7 Conclusion

A growing body of literature highlights significant economist costs of incumbents following a technological shock due to job layoffs or by being forced to take new occupational roles in the same or in a new company. However, it is not clear whether these costs also influence other family members. This paper addresses this issue by studying the labor market implications for icemen following the spread of electric refrigerators into U.S. households. During the 1930s, novel refrigerator models such as the Monitor Top by General Electric emerged as an affordable and reliable substitute for conventional refrigeration methods such as iceboxes. Thus, the demand for manual labor in the ice retailing industry experienced a decline, leading to significant industry disruption. Using linked historical full count census data, I assess not only the implications for the incumbent iceman, but also the intergenerational consequences.

I find that the general spread of electric refrigeration increased the likelihood of incumbents not leaving the ice retail industry and changing occupations. These new occupations were often lower paid, suggesting occupational downgrading, a burden borne mainly by young fathers. In general, the wholesale and retail industry consists of a relatively large share of self-employed individuals, which also applies to ice retailing. The distinction between self-employed and dependent employees reveals various adjustment strategies following a negative demand shock for ice blocks. While the former adjusted within the ice retail industry, the latter sought their fortune outside of it.

Turning the focus on sons, younger cohorts seem to face a tradeoff between labor market participation and school attendance, leading to an average reduction in school attendance rates. This effect is particularly pronounced if the father was previously self-employed but subsequently gave up his business, suggesting that economic constraints forced younger children to contribute to the household income. In contrast, older cohorts are not affected by the technological shock in terms of labor market outcomes, nor does it influence their decision to become self-employed.

The reported results have a important policy implication. Current debates about the costs and benefits of technological change need to consider that the adjustment process at the individual level likely carries significant costs. To reduce these costs, policymakers could consider labor market programs that mitigate income losses (Bessen et al., 2020). However, the results of this study suggest further implications. First, it may not be sufficient to consider only incumbent workers, and programs may require a more comprehensive understanding of affected individuals. Second, within affected industries, individuals may follow different adoption strategies in response to negative shocks. Policymakers need to understand the various underlying incentives to design more appropriate and targeted policies.

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A Data

A.1 Identifying Iceman

IPUMS provides harmonized information on the industry in which individuals worked based on the 1950 Census Bureau industrial classification. This allows for a comparison across census waves, which is essential for this study. Ice retailing is grouped with fuel retailing (industry code 697) within this classification system. To differentiate between the two industries, I use transcribed string information from the original manuscript. The transcribed string information from the original manuscripts are not openly accessible. I obtained restricted access to 20% of each census wave observation , which was sufficient to classify all individuals within the fuel and ice retailing industry. This information is only available from 1910 to 1930 in the sample. String industry information prior to 1910 is unavailable due to the absence of separate treatment of industry and occupation. Consequently, the occupation string for that year is utilized. IPUMS does not provide string information for the industry variable for 1940. This limitation prevents the distinction between the two. However, it does not constitute a significant obstacle, as the primary objective is to determine the treatment status in 1930 and prior years for the empirical analysis.

Identifying ice retailers using string information requires several steps due to the lack of consistent string spelling in the ice retailing industry. It is impractical to manually check each string entry for its relevance, given that approximately 163,000 people were working in the fuel and ice retailing industry in 1930 alone. Therefore, the main idea is to derive a list of strings with different spellings and names that uniquely identify most individuals within the ice retailing industry. First, I classified individuals according to whether they contain any of the following strings in any written combination, irrespectively of the spelling and capitalization: *ice, coal, wood, oil, or office*. I derived this list based on an initial descriptive inspection of strings. Next, individuals only containing the string *ice* were retained. Often, retailers would sell ice and coal, allowing to compensate for changing demand for both goods between seasons. However, the focus of this study is on pure ice retailers, the most affected group of retailers. I also removed observations with the string *office*, which I found to be common based on an initial individual inspection of possible string spellings. Based on the remaining observations, I ranked the string spellings based on absolute counts, maintaining the top 95% of strings. Using the list of top strings, I manually filtered out other misleading strings. Based on this final list of strings, I identified individuals from the ice retailing industry according to whether their industry string matched one of the entries.

A.2 Linking Census Waves

In this paper, I use the deterministic *ABE fully automated linking approach* to create the main dataset, which is described in more detail in Abramitzky et al. (2020).[48][49] Researchers can obtain data access to linkages across census variables from Abramitzky et al. (2021), which provides several versions of linked datasets. The use of first name, last name, age, and place of birth information establish unique pairs of individuals across census waves. The linking algorithm requires several steps, including name cleaning, filtering unique observations, and finding unique pairs, which share the same values as the linking variables. In cases where no pairs can be identified, adjustments for year of birth is an alternative approach. As Abramitzky et al. (2021) demonstrate, an alternative approach involves identifying unique pairs within a 5-year band (within $\pm$ 2 years of implied birth year). A primary concern is the potential for misspelled and mis-transcribed names, resulting in lower numbers of linked individuals. To address this challenge, Abramitzky et al. (2021) provides linkages based on the New York State Identification and Intelligence System (NYSIIS). The NYSISS standardizes names are based on their pronunciation, allowing one to find pairs even in instances of spelling differences.

The following Table A.1 provides an overview of the linkage rates of the sample under investigation with the census 10 years later. It refers to fathers who had at least one son and were within the labor force and specified a working industry within the wholesale and retail industry. Linking probabilities between ice retailing and the rest of the wholesale and retailing industry have similar rates with no systematic differences across decades. For the main sample of 1930, almost one third of observations can be related to observations in 1940.

[48]The computer program for the linking algorithm is publicly available in the following GitHub repository: `https://github.com/historical-record-linking/matching-codes` (accessed March 15, 2025).

[49]The name is derived from the initials of the main authors who improved on the linking algorithm. Abramitzky et al. (2012), Abramitzky et al. (2014), and Abramitzky et al. (2019) applied and tested it.

Table A.1: Linking Probabilities Incumbent Fathers 1900 - 1930

	Ice Retailing		Other Wholesale & Retail Industries	
	N	Mean	N	Mean
1900				
ABE NYSISS	3501	0.25	539476	0.26
1910				
ABE NYSISS	7050	0.27	779549	0.27
1920				
ABE NYSISS	7500	0.31	847796	0.30
1930				
ABE NYSISS	14572	0.32	1101181	0.32

Notes: N reflects the total sample of linked and unlinked fathers. The mean indicates the respective linking rate of the fathers.

The second sample of children also requires linking across census waves. It consists of all sons of the above sample of fathers. However, I do not require their fathers to also be linked across census waves, which would reduce the sample considerably. In addition, conditioning on linked fathers in the linkage procedure would most likely result in a more selective sample because it would amplify the effect of certain individual-level characteristics. For example, if certain surnames of immigrants systematically reduce the probability of being linked, using them in a father and son linking procedure reduces the probability of being linked twice.

The Table A.2 shows the linking probabilities of the sons. Interestingly, the linking probabilities are higher for sons than for fathers. Also, sons of fathers from ice retailing tend to have slightly less successful linkages.

Table A.2: Linking Probabilities Sons 1900 - 1930

	Ice Retailing		Other Wholesale and Retail Industries	
	N	Mean	N	Mean
1900				
ABE NYSISS	5568	0.33	871979	0.35
1910				
ABE NYSISS	10973	0.35	1227645	0.36
1920				
ABE NYSISS	12061	0.36	1324762	0.37
1930				
ABE NYSISS	23726	0.35	1642606	0.37

Notes: N reflects the total sample of linked and unlinked sons. The mean indicates the respective linking rate of the fathers.

A.3 Inverse Probability Weights

I obtain inverse probability weights (IWPs) by estimating the conditional probability of a successful linkage. I base my estimation on the two-step procedure by Feigenbaum and Tan (2020), who adopted the recommendations of Bailey et al. (2020) for historical census data.

The first step involves estimating a conditional probability model. To do so, I run a logit regression. The main variables used to estimate the conditional probability of linkage are the length of the first, middle, and last name; the presence of a middle name; the logarithm of the frequency of occurrence of a first or last name in the census, age; and age squared. Information on household size, number of children, position in household, place of birth, race, and whether someone was married supplement the estimates.

The second step involves the calculation of the inverse probability weights based on the following formula: $IWP = \frac{1-p}{p} \times \frac{m}{1-m}$. p is the estimated linking probability derived from regression model, and m corresponds to the observed linking rate.

I also estimate IWPs for sons, with a minor adjustment to the regression model. I include whether a son has a sibling living in the household and further information on the father's place of birth and race. For sons, I do not include information on marriage.

A.4 Variable Description

Table A.3 – Description of Variables used in this Study

Variable	Definition and Source
$\%\Delta Ind^{\text{ p.C.}}$	Per capita growth rate of the industry size of industry k in county c for year t. Growth rates are calculated based on full count census data from Ruggles et al. (2024).
$\%\Delta Ind$	Growth rate of the industry size of industry k in county c for year t. Growth rates are calculated based on full count census data from Ruggles et al. (2024).
$\Delta Refrig$	Percentage of U. S. households that own n electric refrigerator in 1940. From Haines and ICPSR (2005).
$\Delta Retail$	Growth rate in retail sales between 1929 and 1933 in county c. From Fisback et al. (2005).
Relief Spending	Per capita value of public works and relief spending from 1933 to 1939 in county c. From Fisback et al. (2005).
AAA Grants	Per capita value of agricultural adjustment administration grants in county c. From Fisback et al. (2005).
Avg. Temp. Jan.	30-year mean temperature for the month of January in county c for the period 1901-1930. From Fisback et al. (2005).
Age	Age of the individual. From Ruggles et al. (2024).
Married	Takes a value of one if married and zero otherwise. From Ruggles et al. (2024).
Race	Takes the value of one if white and zero otherwise. From Ruggles et al. (2024).
Literate	Takes a value of one if an individual can read and write and zero otherwise. From Ruggles et al. (2024).
School	Takes a value of one if an individual is still attending an educational institution, and zero otherwise. From Ruggles et al. (2024).
Labor Force	Takes the value of one if an individual is part of the labor force and zero otherwise. No information available for the year 1900. From Ruggles et al. (2024).
Self-Employed	Takes the value of one if an individual is self-employed and zero otherwise. No information available for the year 1900. From Ruggles et al. (2024).

Variable	Definition and Source
Employed	Takes the value of one if employed and zero if unemployed. No information available for the years 1900 and 1920. From Ruggles et al. (2024).
Birthplace	Information on U.S. state of birth or foreign born. From Ruggles et al. (2024).
Foreign Born	Takes the value of one if born outside the United States and zero otherwise. From Ruggles et al. (2024).
Manager	Based on the 1950 Census Bureau occupational classification. Takes a value of one if the occupation code is between 200 and 290, and zero otherwise. From Ruggles et al. (2024).
Laborer	Based on the 1950 Census Bureau occupational classification. Takes a value of one if the occupation code is between 910 and 970, and zero otherwise. From Ruggles et al. (2024).
Wholesale and Retail	Based on the 1950 Census Bureau industrial classification. Takes a value of one if an individual works in an industry with an associated code between 606 and 696, and zero otherwise. From Ruggles et al. (2024).
Migration	Takes a value of one if an individual lives in a different county than in the previous census wave. From Ruggles et al. (2024).
House	Indicates whether the housing unit was owned by one of the residents in which the person lives. Takes the value of one if yes and zero otherwise. From Ruggles et al. (2024).
Farm	Indicates whether a person lived within a farm household. Takes the value of 1 if yes and 0 otherwise. From Ruggles et al. (2024).
Δ Industry	Based on the 1950 Census Bureau industrial classification. Takes a value of one if an individual switched working industry between census waves. Industries based on 1950 industrial codes. From Ruggles et al. (2024).
Δ Occupation	Based on the 1950 Census Bureau occupational classification. Takes a value of one if an individual switched occupations between census waves. From Ruggles et al. (2024).
Occ. Score	For a given occupation it provides the 1950 median total income (in 1950 dollars) of all persons in that occupation. From Ruggles et al. (2024).

Variable	Definition and Source
PRESGL	Reflects the Siegel prestige score associated with an occupation based on the 1950 Census Bureau occupational classification. From Ruggles et al. (2024).
SEI	Reflects the Duncan Socioeconomic Index associated with an occupation based on the 1950 Census Bureau occupational classification. From Ruggles et al. (2024).
LIDO	Adjusted occupational score, correcting for industry and demographic specific effects. From Saavedra and Twinam (2020).

B Figures

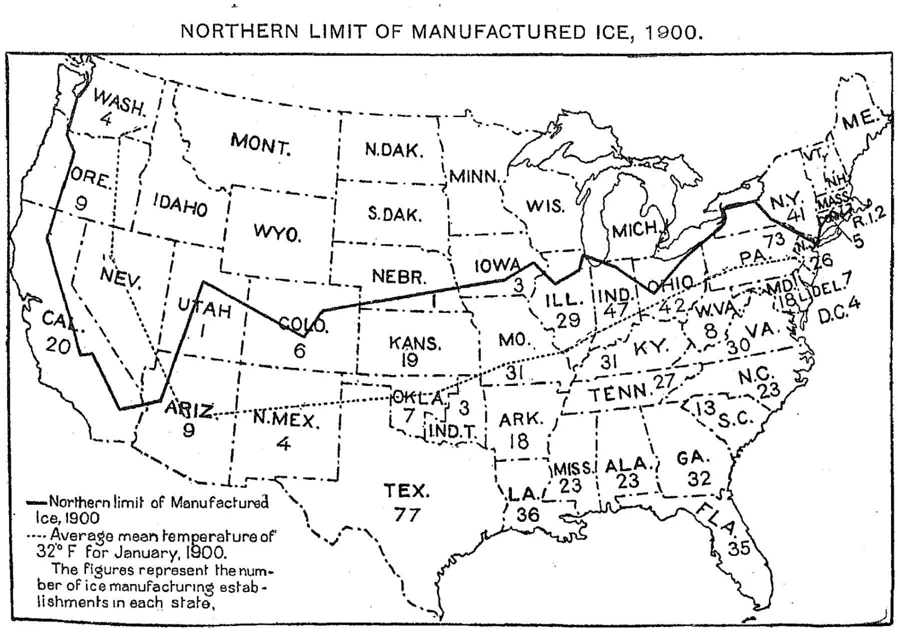


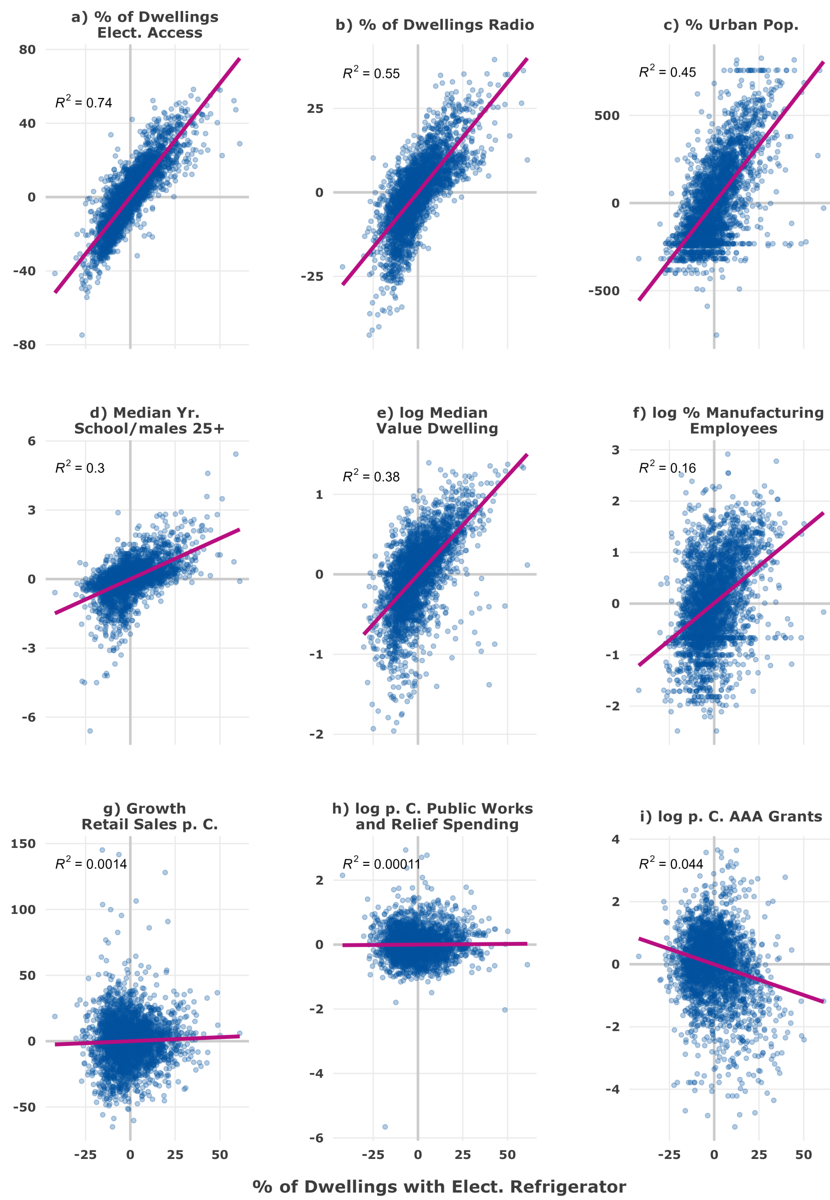
Figure B.1 – Ice Manufacturing 1900

Notes: The map illustrates the distribution of ice manufacturing plants in the United States in 1900. This distribution was correlated with natural geographic conditions, such as average temperature, which influenced the competitiveness of the natural ice industry. *Source: U.S. Bureau of the Census, Census of Manufactures: 1905.*

Figure B.2 – Traditional Icebox (left) and GE's Monitor Top model (right).

Source: Grahn (2015)

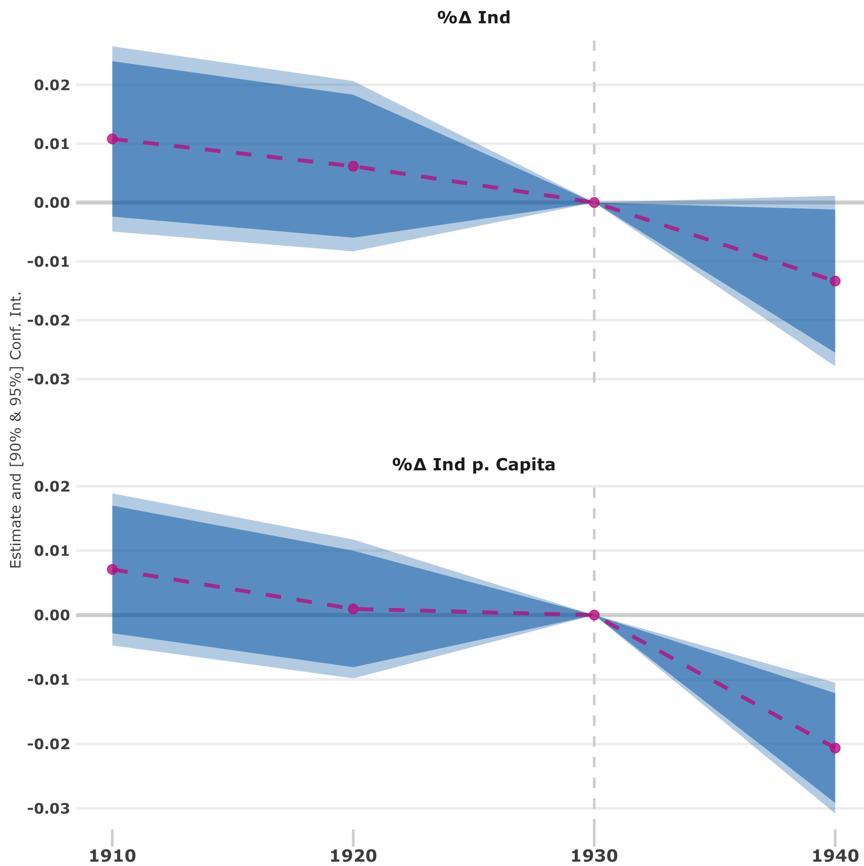
Figure B.3 – Correlations Electric Refrigeration Adoption with other County Variables



Notes: The panels of the figure show different residualized correlations between the share of dwellings with an electric refrigerator and the respective variable at the county level. Residualization was performed at the state level to remove any variation between U.S. states. Panels a) to e) are based on data from the 1940 U.S. census provided in Haines and ICPSR (2005). Panels a) and b) show the correlation with the share of dwellings with access to electricity or a radio. Panel c) shows the correlation with the share of a county's population that is urban, while panel d) shows the correlation with the median years of schooling for males over the age of 25. Panel e) reflects the correlation with the log median value of dwellings in that county. Data for panels f) to i) are taken from Fisback et al. (2005). Panel f) corresponds to the percentage of manufacturing employees in 1929 relative to the adult population in 1930. Panel g) corresponds to the correlation with the growth of retail sales per capita between 1992 and 1933. Panel h) shows the correlation with the log value of per capita public works and relief spending between 1933 and 1939, and panel i) shows the log value of per capita Agricultural Adjustment Administration grants between 1933 and 1938 for a given county.

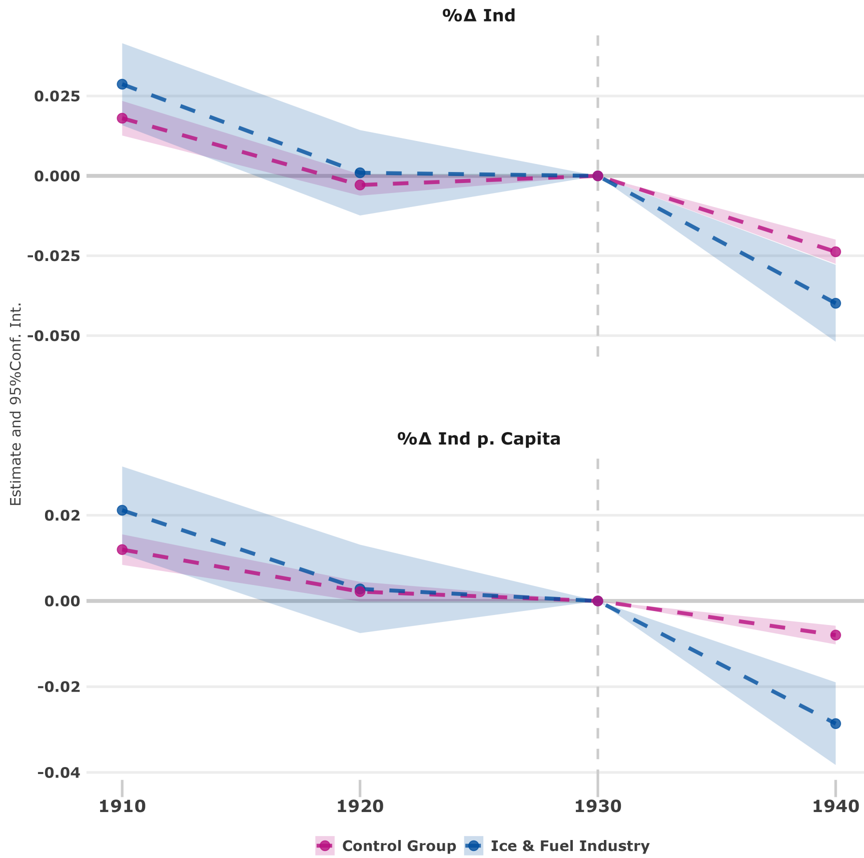
B.1 Figures - Implicit First Stage

Figure B.4 – Event Study - Aggregate Effect of Electric Refrigeration



Notes: **Event study coefficients** and [90% & 95%] **confidence bands** of Equation 1. Estimates are based on the sample from Tables 4 and C.3. Standard errors are clustered at the industry-county level.

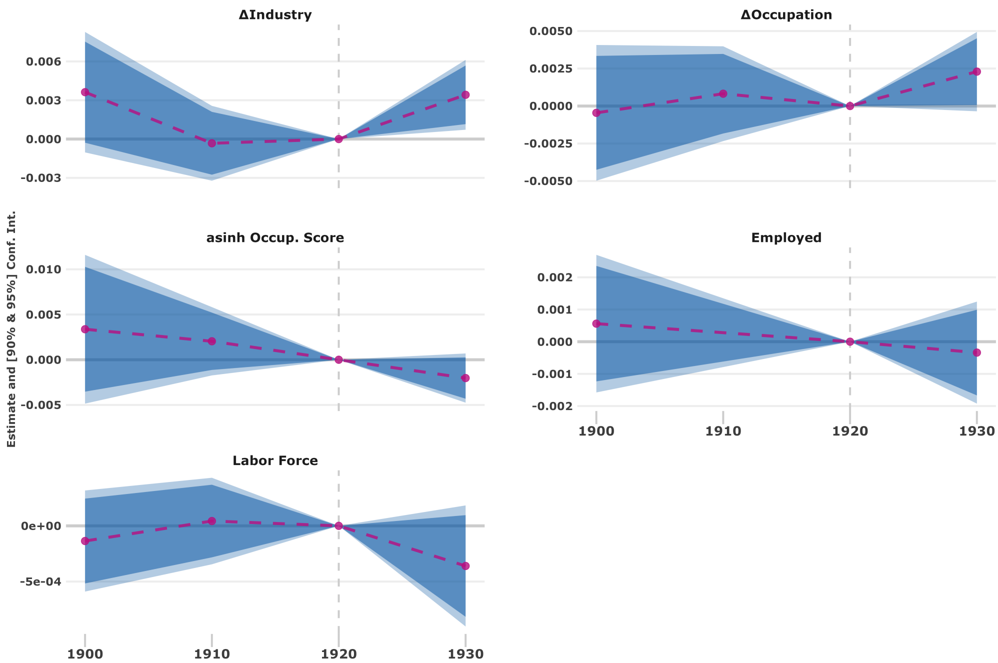
Figure B.5 – Event Study - Decomposing 3DiD Estimates for Aggregate Effect of Electric Refrigeration



Notes: The figure illustrates the idea behind the 3DiD model. Two separate event study regressions are estimated, one for the fuel and ice retailing industry, and one for all other wholesale and retail industries. The dependent variable is the respective industry growth rate (per capita). The models compare the growth rates of the industries over time between counties with high and low levels of adoption in electric refrigeration. **Event study coefficients** and 95% **confidence band** are displayed. Estimates are based on the sample from Tables 4 and C.3. Standard errors are clustered at the industry-county level.

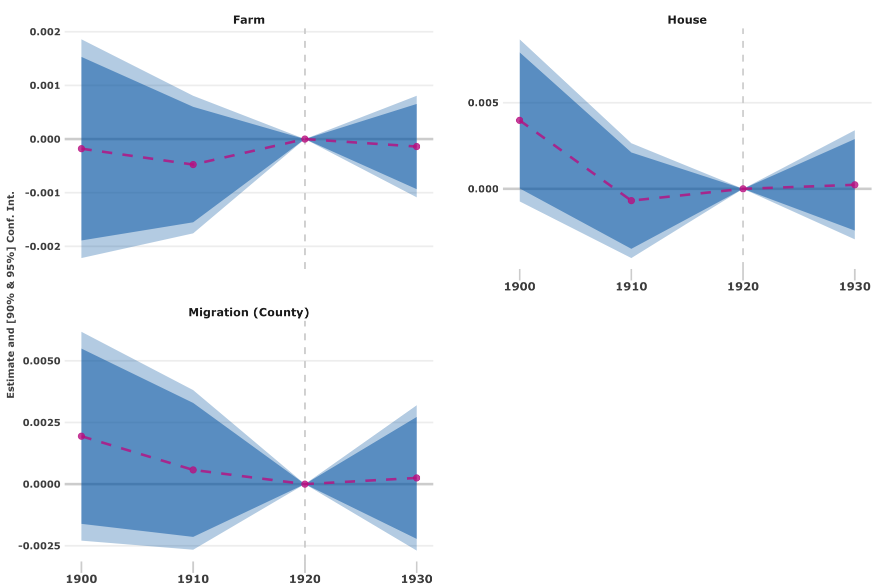
B.2 Figures - Incumbent Fathers

Figure B.6 – Event Study - Labor Market Effect Fathers



Notes: **Event study coefficients** and [90% & 95%] **confidence bands** of Equation 2. Estimates are based on the sample from Table 5. Standard errors are clustered at the industry-county level.

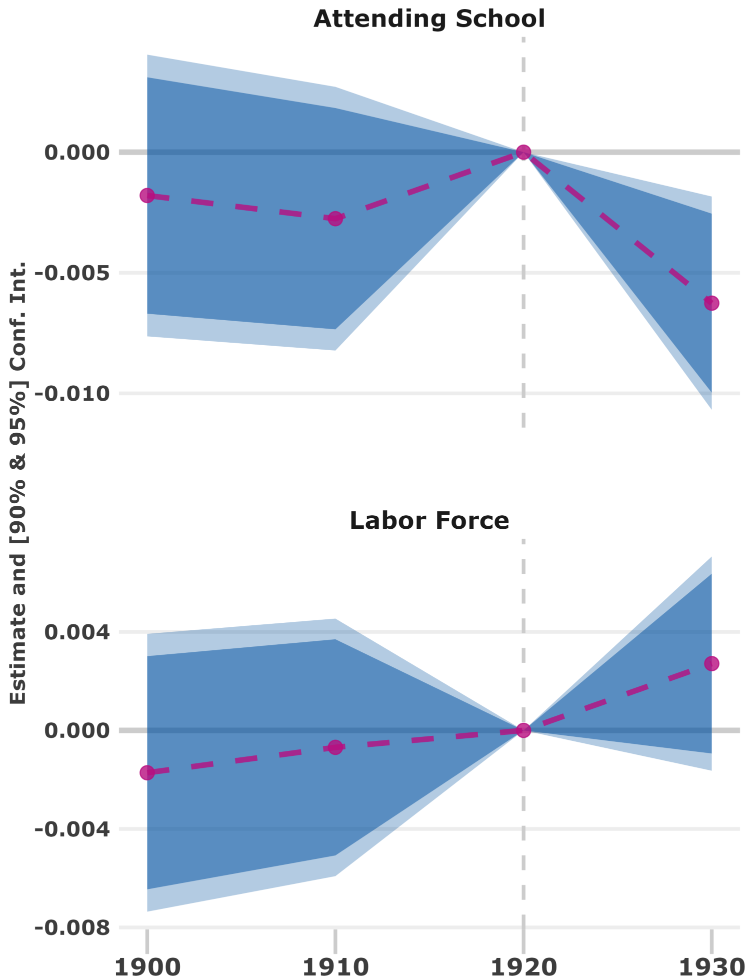
Figure B.7 – Aggregated Employment Effect Ice & Fuel Retail Industry



Notes: **Event study coefficients** and [90% & 95%] **confidence bands** of Equation 2. Estimates are based on the sample from Table 6. Standard errors are clustered at the industry-county level.

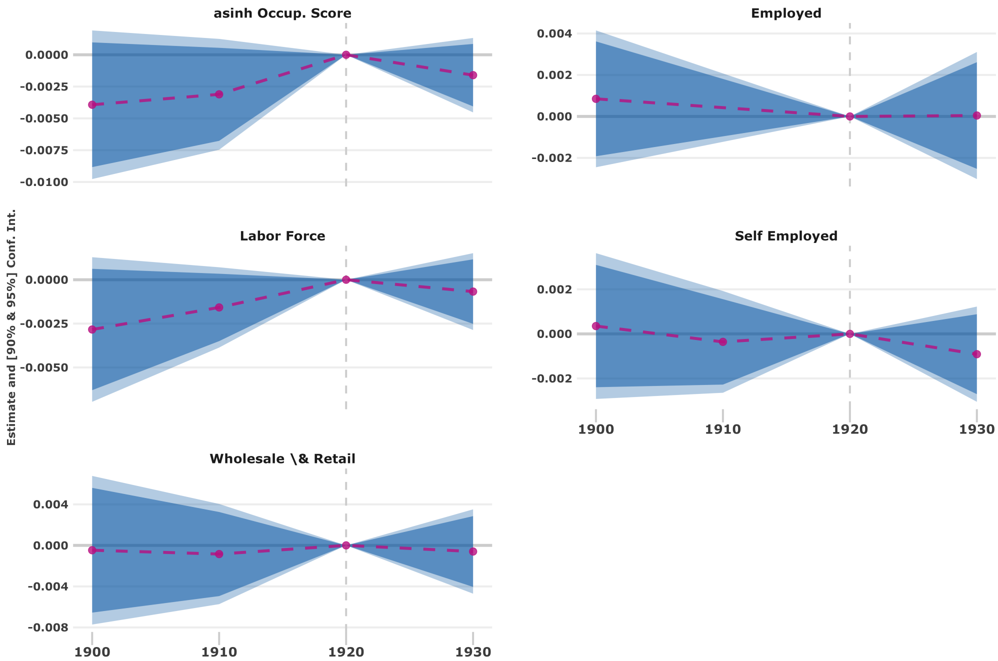
B.3 Figures - Sons

Figure B.8 – Event Study Sons Young Cohort



Notes: **Event study coefficients** and [90% & 95%] **confidence bands**. Standard errors are clustered at the county-industry level of the father.

Figure B.9 – Event Study Sons Old Cohort



Notes: **Event study coefficients** and [90% & 95%] **confidence bands**. Standard errors are clustered at the county-industry level of the father.

C Tables

C.1 Tables Descriptive Statistics

Table C.1: Descriptive Statistics Incumbent Fathers 1900 - 1920

	Ice Retailing						Other Wholesale & Retail Industries					
	N	Mean	SD	Min	Median	Max	N	Mean	SD	Min	Median	Max
1900												
Age	782	36.88	7.91	20.00	36.00	60.00	122443	38.41	8.00	18.00	38.00	60.00
Married	782	0.99	0.09	0.00	1.00	1.00	122443	0.98	0.14	0.00	1.00	1.00
Race	782	0.98	0.12	0.00	1.00	1.00	122443	0.99	0.10	0.00	1.00	1.00
Literate	782	0.97	0.18	0.00	1.00	1.00	122443	0.97	0.17	0.00	1.00	1.00
Labor Force	0						0					
Employed	0						0					
Self-employed	0						0					
Foreign Born	782	0.24	0.42	0.00	0.00	1.00	122427	0.30	0.46	0.00	0.00	1.00
Manager	782	0.53	0.50	0.00	1.00	1.00	122443	0.50	0.50	0.00	1.00	1.00
Laborer	782	0.03	0.16	0.00	0.00	1.00	122443	0.01	0.09	0.00	0.00	1.00
Farm	782	0.05	0.22	0.00	0.00	1.00	122443	0.06	0.23	0.00	0.00	1.00
Dwelling	782	0.38	0.48	0.00	0.00	1.00	122443	0.45	0.50	0.00	0.00	1.00
Occ. Score	782	33.61	9.67	13.00	42.00	42.00	122443	33.26	9.06	3.00	40.00	80.00
PRESGL	782	38.91	12.57	12.20	50.30	50.30	122443	41.73	10.24	12.20	50.30	81.50
SEI	782	49.04	21.53	8.00	68.00	68.00	122443	52.12	19.15	4.00	68.00	92.00
LIDO	769	26.35	3.47	13.82	29.47	29.47	121265	27.17	6.10	5.19	26.69	89.44
1910												
Age	1577	36.12	8.00	19.00	36.00	60.00	173354	38.29	8.18	18.00	38.00	60.00
Married	1577	0.99	0.11	0.00	1.00	1.00	173354	0.98	0.13	0.00	1.00	1.00
Race	1577	0.96	0.20	0.00	1.00	1.00	173354	0.98	0.13	0.00	1.00	1.00
Literate	1577	0.97	0.18	0.00	1.00	1.00	173354	0.98	0.15	0.00	1.00	1.00
Labor Force	1577	1.00	0.00	1.00	1.00	1.00	173354	1.00	0.00	1.00	1.00	1.00
Employed	1577	0.97	0.17	0.00	1.00	1.00	173354	0.97	0.17	0.00	1.00	1.00
Self-employed	1577	0.19	0.40	0.00	0.00	1.00	173354	0.49	0.50	0.00	0.00	1.00
Foreign Born	1577	0.22	0.42	0.00	0.00	1.00	173348	0.30	0.46	0.00	0.00	1.00
Manager	1577	0.20	0.40	0.00	0.00	1.00	173354	0.43	0.49	0.00	0.00	1.00
Laborer	1577	0.28	0.45	0.00	0.00	1.00	173354	0.04	0.20	0.00	0.00	1.00
Farm	1577	0.02	0.15	0.00	0.00	1.00	173354	0.04	0.20	0.00	0.00	1.00
Dwelling	1577	0.31	0.46	0.00	0.00	1.00	173354	0.45	0.50	0.00	0.00	1.00
Occ. Score	1577	27.00	9.36	6.00	27.00	63.00	173354	32.08	9.51	3.00	29.00	80.00
PRESGL	1577	29.65	13.26	12.20	28.00	73.60	173354	40.09	11.25	0.00	41.20	81.50
SEI	1577	33.27	21.65	6.00	32.00	96.00	173354	48.45	21.15	4.00	47.00	96.00
LIDO	1509	23.67	3.61	11.04	23.07	29.47	160075	27.38	6.06	4.63	27.00	90.25
1920												
Age	1921	36.93	8.13	18.00	36.00	60.00	213475	38.26	8.23	18.00	38.00	60.00
Married	1921	0.98	0.13	0.00	1.00	1.00	213475	0.98	0.13	0.00	1.00	1.00
Race	1921	0.96	0.19	0.00	1.00	1.00	213475	0.98	0.13	0.00	1.00	1.00
Literate	1921	0.96	0.19	0.00	1.00	1.00	213475	0.98	0.15	0.00	1.00	1.00
Labor Force	1921	1.00	0.00	1.00	1.00	1.00	213475	1.00	0.00	1.00	1.00	1.00
Employed	0						0					
Self-employed	1921	0.19	0.40	0.00	0.00	1.00	213475	0.44	0.50	0.00	0.00	1.00
Foreign Born	1921	0.25	0.43	0.00	0.00	1.00	213474	0.30	0.46	0.00	0.00	1.00
Manager	1921	0.21	0.41	0.00	0.00	1.00	213475	0.43	0.49	0.00	0.00	1.00
Laborer	1921	0.29	0.45	0.00	0.00	1.00	213475	0.04	0.20	0.00	0.00	1.00
Farm	1921	0.01	0.12	0.00	0.00	1.00	213475	0.03	0.17	0.00	0.00	1.00
Dwelling	1921	0.34	0.47	0.00	0.00	1.00	213475	0.47	0.50	0.00	0.00	1.00
Occ. Score	1921	27.82	9.16	6.00	27.00	46.00	213475	32.18	9.42	3.00	29.00	80.00
PRESGL	1921	30.85	13.23	12.20	28.00	69.00	213475	40.51	10.98	0.00	41.20	81.50
SEI	1921	33.48	22.36	7.00	32.00	84.00	213475	48.78	21.23	3.00	47.00	96.00
LIDO	1767	23.56	3.71	12.27	23.07	29.47	196757	27.76	6.25	4.23	27.21	90.25

Notes: Descriptive statistics based on sample used in Table 5. No information on labor force, employment, and self-employment status is available for 1900. No employment information is available for 1920.

Table C.2: Descriptive Statistics Sons 1900-1920

	Ice Retailing						Other Wholesale & Retail Industries					
	N	Mean	SD	Min	Median	Max	N	Mean	SD	Min	Median	Max
1900												
Age	983	10.55	3.31	6.00	10.00	17.00	160127	10.69	3.40	6.00	10.00	17.00
Race	983	0.98	0.15	0.00	1.00	1.00	160127	0.99	0.10	0.00	1.00	1.00
Literate	983	0.52	0.50	0.00	1.00	1.00	160127	0.55	0.50	0.00	1.00	1.00
Foreign Born	983	0.03	0.18	0.00	0.00	1.00	160127	0.05	0.23	0.00	0.00	1.00
School	983	0.75	0.44	0.00	1.00	1.00	160071	0.76	0.43	0.00	1.00	1.00
Labor Force	0						0					
1910												
Age	1815	10.68	3.35	6.00	10.00	17.00	222464	10.94	3.45	6.00	11.00	17.00
Race	1815	0.97	0.18	0.00	1.00	1.00	222464	0.98	0.13	0.00	1.00	1.00
Literate	1815	0.55	0.50	0.00	1.00	1.00	222464	0.57	0.50	0.00	1.00	1.00
Foreign Born	1815	0.03	0.17	0.00	0.00	1.00	222464	0.06	0.23	0.00	0.00	1.00
School	1815	0.89	0.32	0.00	1.00	1.00	222464	0.90	0.31	0.00	1.00	1.00
Labor Force	218	0.64	0.48	0.00	1.00	1.00	29958	0.53	0.50	0.00	1.00	1.00
1920												
Age	2241	10.58	3.39	6.00	10.00	17.00	263619	10.82	3.44	6.00	10.00	17.00
Race	2241	0.96	0.19	0.00	1.00	1.00	263619	0.98	0.13	0.00	1.00	1.00
Literate	2241	0.54	0.50	0.00	1.00	1.00	263619	0.57	0.50	0.00	1.00	1.00
Foreign Born	2241	0.03	0.18	0.00	0.00	1.00	263619	0.04	0.19	0.00	0.00	1.00
School	2241	0.83	0.37	0.00	1.00	1.00	263619	0.87	0.34	0.00	1.00	1.00
Labor Force	254	0.64	0.48	0.00	1.00	1.00	33826	0.47	0.50	0.00	0.00	1.00

Notes: Descriptive statistics are based on samples used in Tables 8 & 9. Lower numbers for labor force status occur because information is only available starting at age 16.

C.2 Tables Implicit First Stage

Table C.3 – Implicit First Stage: Aggregated Growth Effects Ice & Fuel

			$\%\Delta Ind$		
	(1)	(2)	(3)	(4)	(5)
$\Delta Refrig\times$ Ice & Fuel Ind. $\times$ Post 1930	-0.018***	-0.019***	-0.018***	-0.015**	
	(0.006)	(0.007)	(0.007)	(0.007)	
$\%\Delta Retail\times$ Ice & Fuel Ind. $\times$ Post 1930		0.006			
		(0.006)			
Relief Spending $\times$ Ice & Fuel Ind. $\times$ Post 1930		0.142			
		(0.221)			
AAA Grants $\times$ Ice & Fuel Ind. $\times$ Post 1930		0.103			
		(0.102)			
Avg. Temp. Jan. $\times$ Ice & Fuel Ind. $\times$ Post 1930			-0.060		
			(0.038)		
Refrig^G $\times$ Ice & Fuel Ind. $\times$ Post 1930					-0.160***
					(0.036)
Mean Y (Ice & Fuel Ind. 1930)	0.657	0.657	0.657	0.657	0.657
County-Year FE	Yes	Yes	Yes	Yes	Yes
County-Industry FE	Yes	Yes	Yes	Yes	Yes
State-Industry-Year FE	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.28726	0.29030	0.28668	0.27350	0.28726
Observations	802,112	772,842	799,869	661,782	802,112

Notes: The dependent variable is the industry growth rate for all columns. Column 2 controls for further variables related to the Great Depression. These include the growth rate in retail sales between 1929 and 1933 as a proxy for the severity of the crisis, public work and relief spending per capita, and AAA grants per capita. The third column incorporates the 30-year mean temperature for the month of January at the county level, while the fourth column removes all observations from states that did not have an ice manufacturing industry in 1900. The fifth column employs a transformation of the main variable, $\Delta Refrig_c$, by reflecting the decile, ranging from 1 to 10. Standard errors are clustered at the industry-county level and reported in parentheses. The specified mean value reflects the average county growth rate of the ice & fuel industry between 1920 and 1930. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

C.3 Tables Incumbent Fathers

Table C.4 – Robustness Different Income/Wage Variables

	log Lido Score (1)	asinh Siegel Score (2)	asinh Duncon Index (3)
$\Delta Refrig\times$ Ice Ind. $\times$ Post 1920	-0.0015* (0.0009)	-0.0033*** (0.0013)	-0.0077*** (0.0021)
Year-County FE	Yes	Yes	Yes
Industry-Year-State FE	Yes	Yes	Yes
County-Industry FE	Yes	Yes	Yes
Literate FE	Yes	Yes	Yes
Age Bin FE	Yes	Yes	Yes
Citizen FE	Yes	Yes	Yes
Race FE	Yes	Yes	Yes
Married FE	Yes	Yes	Yes
Birthplace FE	Yes	Yes	Yes
R^2	0.24681	0.10912	0.13670
Observations	814,308	814,308	814,308

Notes: In the first column, the natural logarithm of the Lido Score is calculated. The inverse hyperbolic sine transformation is employed in Columns 2 and 3 for the Siegel Score and the Duncon Index. It is used as an approximation to the logarithm due to the occurrence of zero values. Standard errors are clustered at the industry-county level and reported in parentheses.* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table C.5 – Robustness without Control Variables

	$\Delta Industry$ (1)	$\Delta Occupation$ (2)	asinh Occup. Score (3)	Employed (4)	Labor Force (5)	Self-Employed (6)
$\Delta Refrig\times$ Ice Ind. $\times$ Post 1920	0.0027** (0.0011)	0.0019* (0.0010)	-0.0032*** (0.0012)	-0.0005 (0.0007)	-0.0004 (0.0003)	0.0010 (0.0012)
Year-County FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry-Year-State FE	Yes	Yes	Yes	Yes	Yes	Yes
County-Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.15131	0.09154	0.10969	0.07694	0.07081	0.13587
Observations	814,308	814,308	814,308	627,497	814,308	814,308

Notes: The dependent variables in Columns 1, 2, 4-6 are binary. Column 1 indicates whether a father switched industries, and Column 2 indicates whether he switched occupations (yes = 1). Column 3 takes the inverse hyperbolic sine transformation of the occupation score as an approximation to the logarithm due to the occurrence of zero values. Column 4 focuses on whether someone continues to have an employment (yes = 1). Similarly, Columns 5 and 6 focus on the labor force and self-employment status, respectively. It should be noted that observations in Column 4 are lower due to the absence of employment information for the year 1920. Standard errors are clustered at the industry-county level and reported in parentheses. The regressions do not include individual level controls.* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table C.6 – Robustness Conditionally on being Employed

	$\Delta Industry$ (1)	$\Delta Occupation$ (2)	asinh Occup. Score (3)	Employed (4)	Labor Force (5)	Self-Employed (6)
$\Delta Refrig\times$ Ice Ind. $\times$ Post 1920	0.0054***	0.0027*	-0.0046***	-1.1313	-0.0003	-0.0007
	(0.0015)	(0.0015)	(0.0016)	(177.7564)	(0.0004)	(0.0018)
Year-County FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry-Year-State FE	Yes	Yes	Yes	Yes	Yes	Yes
County-Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Literate FE	Yes	Yes	Yes	Yes	Yes	Yes
Age Bin FE	Yes	Yes	Yes	Yes	Yes	Yes
Citizen FE	Yes	Yes	Yes	Yes	Yes	Yes
Race FE	Yes	Yes	Yes	Yes	Yes	Yes
Married FE	Yes	Yes	Yes	Yes	Yes	Yes
Birthplace FE	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.16493	0.11969	0.13383	0.10602	0.09465	0.17405
Observations	462,860	462,860	462,860	288,670	462,860	462,860

Notes: The dependent variables in Columns 1, 2, and 4-6 are binary. Column 1 indicates whether a father switched industries, and Column 2 indicates whether he switched occupations (yes = 1). Column 3 takes the inverse hyperbolic sine transformation of the occupation score as an approximation to the logarithm due to the occurrence of zero values. Column 4 focuses on whether someone continues to have an employment (yes = 1). Similarly, Columns 5 and 6 focus on the labor force and self-employment status, respectively. It should be noted that observations in Column 4 are lower due to the absence of employment information for the year 1920. Standard errors are clustered at the industry-county level and reported in parentheses. The sample is conditionally on being emloyed in year t. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table C.7 – Robustness Balanced Panel of Fathers 1920-1940

	$\Delta Industry$ (1)	$\Delta Occupation$ (2)	asinh Occup. Score (3)	Employed (4)	Labor Force (5)	Self-Employed (6)
$\Delta Refrig\times$ Ice Ind. $\times$ Post 1930	0.0023***	0.0029***	-0.0026*	-0.0009	-0.0003	-0.0009
	(0.0008)	(0.0010)	(0.0014)	(0.0005)	(0.0002)	(0.0010)
Year-main_county_fe FE	Yes	Yes	Yes	Yes	Yes	Yes
main_industry-Year FE	Yes	Yes	Yes	Yes	Yes	Yes
main_county_fe-main_industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Literate FE	Yes	Yes	Yes	Yes	Yes	Yes
Age Bin FE	Yes	Yes	Yes	Yes	Yes	Yes
Citizen FE	Yes	Yes	Yes	Yes	Yes	Yes
Race FE	Yes	Yes	Yes	Yes	Yes	Yes
Married FE	Yes	Yes	Yes	Yes	Yes	Yes
Birthplace FE	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.19801	0.16689	0.19287	0.09922	0.10874	0.21409
Observations	267,370	267,370	401,055	264,719	401,055	401,055

Notes: The dependent variables in Columns 1, 2, and 4-6 are binary. Column 1 indicates whether a father switched industries, and Column 2 indicates whether he switched occupations (yes = 1). Column 3 takes the inverse hyperbolic sine transformation of the occupation score as an approximation to the logarithm due to the occurrence of zero values. Column 4 focuses on whether someone continues to have an employment (yes = 1). Similarly, Columns 5 and 6 focus on the labor force and self-employment status, respectively. It should be noted that observations in Column 4 are lower due to the absence of employment information for the year 1920. Standard errors are clustered at the industry-county level and reported in parentheses. Due to the linkage across three census waves and the resulting reduced number of observations, I consider a less conservative fixed effects specification with only industry-year fixed effects. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table C.8 – Labor Market Effects - Inverse Probability Weights

	$\Delta Industry$ (1)	$\Delta Occupation$ (2)	asinh Occup. Score (3)	Employed (4)	Labor Force (5)	Self-Employed (6)
$\Delta Refrig\times$ Ice Ind. $\times$ Post 1920	0.0030***	0.0018*	-0.0031**	-0.0005	-0.0005	0.0006
	(0.0011)	(0.0010)	(0.0012)	(0.0007)	(0.0003)	(0.0013)
Year-County FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry-Year-State FE	Yes	Yes	Yes	Yes	Yes	Yes
County-Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Literate FE	Yes	Yes	Yes	Yes	Yes	Yes
Age Bin FE	Yes	Yes	Yes	Yes	Yes	Yes
Citizen FE	Yes	Yes	Yes	Yes	Yes	Yes
Race FE	Yes	Yes	Yes	Yes	Yes	Yes
Married FE	Yes	Yes	Yes	Yes	Yes	Yes
Birthplace FE	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.15091	0.09974	0.12121	0.07972	0.07823	0.14711
Observations	814,308	814,308	814,308	627,497	814,308	814,308

Notes: The dependent variables in Columns 1, 2, and 4-6 are binary. Column 1 indicates whether a father switched industries, and Column 2 indicates whether he switched occupations (yes = 1). Column 3 takes the inverse hyperbolic sine transformation of the occupation score as an approximation to the logarithm due to the occurrence of zero values. Column 4 focuses on whether someone continues to have an employment (yes = 1). Similarly, Columns 5 and 6 focus on the labor force and self-employment status, respectively. It should be noted that observations in Column 4 are lower due to the absence of employment information for the year 1920. Standard errors are clustered at the industry-county level and reported in parentheses. Estimates are weighted with inverse probability weights to control for potentially biased and unrepresentative samples due to census linking. See Section A.3 in the Appendix on how these weights are calculated. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table C.9 – Census Linking Probability

	NYSIIS Linking (1)	(2)
$\Delta Refrig\times$ Ice Ind. $\times$ Post 1920	0.0003	0.0004
	(0.0005)	(0.0005)
Year-County FE	Yes	Yes
Industry-Year-State FE	Yes	Yes
County-Industry FE	Yes	Yes
Literate FE		Yes
Age Bin FE		Yes
Citizen FE		Yes
Race FE		Yes
Married FE		Yes
Birthplace FE		Yes
R^2	0.04182	0.05414
Observations	3,299,784	3,299,784

Notes: The dependent variable is a binary indicator that takes the value of 1 if an individual was linked between census waves. The sample includes all males aged 18 and over who report any industry within wholesale and retail trade as their place of work. Standard errors are clustered at the industry-county level and reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table C.10 – Labor Market Effects by Self-Employment Status

	$\Delta Industry$		$\Delta Occupation$		asinh Occup. Score		Labor Force		Employed		Self-Employed	
	Dependent	Self-Employed	Dependent	Self-Employed	Dependent	Self-Employed	Dependent	Self-Employed	Dependent	Self-Employed	Dependent	Self-Employed
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
$\Delta Refrig \times$ Ice Ind. $\times$ Post 1920	0.0037***	-0.0004	0.0018	0.0042	-0.0019	-0.0048	-0.0004	-0.0013	-0.0011	0.0035*	0.0017	-0.0077**
	(0.0014)	(0.0041)	(0.0012)	(0.0027)	(0.0013)	(0.0040)	(0.0003)	(0.0009)	(0.0009)	(0.0020)	(0.0014)	(0.0039)
Year-County FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry-Year-State FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
County-Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Literate FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Age Bin FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Citizen FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Race FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Married FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Birthplace FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.18191	0.18470	0.12759	0.16460	0.16174	0.16739	0.10999	0.12627	0.11111	0.13326	0.16509	0.15776
Observations	405,391	287,328	405,391	287,328	405,391	287,328	405,391	287,328	313,055	198,909	405,391	287,328

Notes: Columns 1-12 contain the same variables as in Table eftab:father table 1. The sample is split by self-employment status. Information on self-employment status is available from 1910, which reduces the total sample size compared to Table eftab:father table 1. Also, note that the observations in Columns 10 and 11 are lower due to the lack of employment information for 1920. Standard errors are clustered at the industry-county level and reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table C.11 – Labor Market Effects by Self-Employment Status Conditional on Labor Force Participation

	$\Delta Industry$		$\Delta Occupation$		asinh Occup. Score		Self-Employed	
	Dependent	Self-Employed	Dependent	Self-Employed	Dependent	Self-Employed	Dependent	Self-Employed
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\Delta Refrig\times$ Ice Ind. $\times$ Post 1920	0.0035**	-0.0015	0.0019	0.0039	-0.0017	-0.0014	0.0018	-0.0068*
	(0.0014)	(0.0041)	(0.0013)	(0.0028)	(0.0013)	(0.0032)	(0.0014)	(0.0039)
Year-County FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry-Year-State FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
County-Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Literate FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Age Bin FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Citizen FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Race FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Married FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Birthplace FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.18309	0.18633	0.12874	0.16617	0.18835	0.20592	0.16600	0.15940
Observations	400,690	283,549	400,690	283,549	400,690	283,549	400,690	283,549

Notes: Columns 1-12 contain the same variables as in Table eftab:father table 1. The sample is split by self-employment status. Information on self-employment status is available from 1910, which reduces the total sample size compared to Table eftab:father table 1. The regesssion condition on being in the labor force ten years later. Also note that the observations in Columns 10 and 11 are lower due to the lack of employment information for 1920. Standard errors are clustered at the industry-county level and reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

C.4 Tables Sons

Table C.12 – Linking Probability of Sons

	NYSIIS Linking	
	ABE NYSIIS	
	(1)	(2)
$\Delta Refrig \times$ Ice Ind. Father $\times$ Post 1920	-0.0005	-0.0004
	(0.0005)	(0.0005)
Year-County Father FE	Yes	Yes
Industry Father-Year-State Father FE	Yes	Yes
County Father-Industry Father FE	Yes	Yes
Literate Father FE		Yes
Age Bin Father FE		Yes
Citizen Father FE		Yes
Race Father FE		Yes
Married Father FE		Yes
Birthplace Father FE		Yes
Literate FE		Yes
R^2	0.03719	0.04205
Observations	5,118,014	5,118,014

Notes: The dependent variable is a binary indicator that takes the value of 1 if an individual was linked between census waves. The sample includes all sons of fathers who worked in wholesale and retail trade and are under the age of 18. Standard errors are clustered at the industry-county level of the fathers and reported in parentheses.* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table C.13 – School Attendance and Labor Force Participation of the Young Cohort - Inverse Probability Weights

	Attending School (1)	Labor Force (2)
$\Delta Refrig\times$ Ice Ind. Father $\times$ Post 1920	-0.0039**	0.0024
	(0.0019)	(0.0019)
Year-County Father FE	Yes	Yes
Industry Father-Year-State Father FE	Yes	Yes
County Father-Industry Father FE	Yes	Yes
Literate Father FE	Yes	Yes
Age Bin Father FE	Yes	Yes
Citizen Father FE	Yes	Yes
Race Father FE	Yes	Yes
Married Father FE	Yes	Yes
Birthplace Father FE	Yes	Yes
Literate FE	Yes	Yes
R^2	0.18592	0.19053
Observations	427,551	427,551

Notes: Both dependent variables are binary. Column 1 indicates whether a son is still in school (yes = 1), and Column 2 indicates whether a son is in the labor force (yes = 1). Estimates are weighted with inverse probability weights to control for potentially biased and unrepresentative samples due to census linking. See Section A.3 in the Appendix on how these weights are calculated. Standard errors are clustered at the industry-county level of the father and reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table C.14 – School Attendance and Labor Force Participation of the Young Cohort by Self-Employment Status of the Father

	Attending School		Labor Force	
	Dependent Employee	Self-Employed	Dependent Employee	Self-Employed
	(1)	(2)	(3)	(4)
$\Delta Refrig\times$ Ice Ind. Father × Post 1920	-0.0031	-0.0090**	0.0032	0.0048
	(0.0025)	(0.0035)	(0.0027)	(0.0053)
Year-County Father FE	Yes	Yes	Yes	Yes
Industry Father-Year-State Father FE	Yes	Yes	Yes	Yes
County Father-Industry Father FE	Yes	Yes	Yes	Yes
Literate Father FE	Yes	Yes	Yes	Yes
Age Bin Father FE	Yes	Yes	Yes	Yes
Citizen Father FE	Yes	Yes	Yes	Yes
Race Father FE	Yes	Yes	Yes	Yes
Married Father FE	Yes	Yes	Yes	Yes
Birthplace Father FE	Yes	Yes	Yes	Yes
Literate FE	Yes	Yes	Yes	Yes
R^2	0.24968	0.25722	0.24139	0.24836
Observations	196,648	159,379	196,648	159,379

Notes: Both dependent variables are binary. Column 1 indicates whether a son is still in school (yes = 1), and Column 2 indicates whether a son is in the labor force (yes = 1). The sample is split along the self-employment status of the father. Information on self-employment status is available from 1910, which reduces the total sample size compared to Table 8. Standard errors are clustered at the industry-county level of the father and reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table C.15 – Effect on Young Cohort of Self-Employed Fathers - Staying in vs. Leaving Self-Employment

	Attending School		Labor Force	
	Non-Dropout	Dropout	Non-Dropout	Dropout
	(1)	(2)	(3)	(4)
$\Delta Refrig\times$ Ice Ind. Father $\times$ Post 1920	0.0032	-0.0095*	-0.0133	0.0071
	(0.0084)	(0.0049)	(0.0086)	(0.0065)
Year-County Father FE	Yes	Yes	Yes	Yes
Industry Father-Year-State Father FE	Yes	Yes	Yes	Yes
County Father-Industry Father FE	Yes	Yes	Yes	Yes
Literate Father FE	Yes	Yes	Yes	Yes
Age Bin Father FE	Yes	Yes	Yes	Yes
Citizen Father FE	Yes	Yes	Yes	Yes
Race Father FE	Yes	Yes	Yes	Yes
Married Father FE	Yes	Yes	Yes	Yes
Birthplace Father FE	Yes	Yes	Yes	Yes
Literate FE	Yes	Yes	Yes	Yes
R^2	0.25740	0.25736	0.24849	0.24850
Observations	158,913	158,899	158,913	158,899

Notes: Both dependent variables are binary. Columns 1 and 2 estimate whether a son is still in school (yes = 1), and Columns 3 and 4 estimate whether a son is in the labor force (yes = 1). The sample consists only of fathers who were self-employed. Columns 1 and 3 do not include fathers in ice retailing who left self-employment after 1930. Columns 2 and 4 do not include fathers in ice retailing who remained self-employed after 1930. Standard errors are clustered at the industry-county level of the father and reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table C.16 – Labor Market Effect Sons Older Cohort by Self-Employment Status of Fathers

	Labor Force		Employed		asinh Occup. Score		Self-Employed		Wholesale & Retail	
	Dependent Employee	Self-Employed	Dependent Employee	Self-Employed	Dependent Employee	Self-Employed	Dependent Employee	Self-Employed	Dependent Employee	Self-Employed
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
$\Delta Refrig \times$ Ice Ind. Father $\times$ Post 1920	-0.0012	0.0029	0.0000	0.0025	-0.0013	0.0026	0.0000	-0.0015	-0.0025	0.0011
	(0.0013)	(0.0024)	(0.0023)	(0.0021)	(0.0016)	(0.0029)	(0.0012)	(0.0028)	(0.0022)	(0.0041)
Year-County Father FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry Father-Year-State Father FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
County Father-Industry Father FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Literate Father FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Age Bin Father FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Citizen Father FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Race Father FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Married Father FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Birthplace Father FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Literate FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.14467	0.15973	0.15610	0.15575	0.25668	0.24019	0.22034	0.20139	0.17947	0.18454
Observations	242,381	236,709	173,715	151,219	225,630	217,039	225,630	217,039	225,630	217,039

Notes: The sample is split along the self-employment status of the father. Information on self-employment status is available from 1910, which reduces the total sample size compared to Table 9. Standard errors are clustered at the industry-county level of the father and reported in parentheses.* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table C.17 – Alternative Income Measures Sons Older Cohort

	log Lido Score (1)	asinh Siegel Score (2)	asinh Duncon Index (3)
$\Delta Refrig \times$ Ice Ind. Father $\times$ Post 1920	0.0004	0.0011	-0.0008
	(0.0008)	(0.0017)	(0.0025)
Year-County Father FE	Yes	Yes	Yes
Industry Father-Year-State Father FE	Yes	Yes	Yes
County Father-Industry Father FE	Yes	Yes	Yes
Literate Father FE	Yes	Yes	Yes
Age Bin Father FE	Yes	Yes	Yes
Citizen Father FE	Yes	Yes	Yes
Race Father FE	Yes	Yes	Yes
Married Father FE	Yes	Yes	Yes
Birthplace Father FE	Yes	Yes	Yes
Literate FE	Yes	Yes	Yes
R^2	0.26569	0.14857	0.18216
Observations	523,370	523,370	523,370

Notes: In the first column, the natural logarithm of the Lido Score is calculated. The inverse hyperbolic sine transformation is employed in Columns 2 and 3 for the Siegel Score and the Duncon Index. It is used as an approximation to the logarithm due to the occurrence of zero values. Standard errors are clustered at the industry-county level of the father and reported in parentheses.* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table C.18 – Labor Market Effects Sons Older Cohort - Inverse Probability Weights

	Labor Force (1)	Employed (2)	asinh Occup. Score (3)	Self-Employed (4)	Wholesale & Retail (5)
$\Delta Refrig \times$ Ice Ind. Father $\times$ Post 1920	0.0004	-0.0005	0.0002	-0.0007	-0.0006
	(0.0010)	(0.0014)	(0.0011)	(0.0009)	(0.0017)
Year-County Father FE	Yes	Yes	Yes	Yes	Yes
Industry Father-Year-State Father FE	Yes	Yes	Yes	Yes	Yes
County Father-Industry Father FE	Yes	Yes	Yes	Yes	Yes
Literate Father FE	Yes	Yes	Yes	Yes	Yes
Age Bin Father FE	Yes	Yes	Yes	Yes	Yes
Citizen Father FE	Yes	Yes	Yes	Yes	Yes
Race Father FE	Yes	Yes	Yes	Yes	Yes
Married Father FE	Yes	Yes	Yes	Yes	Yes
Birthplace Father FE	Yes	Yes	Yes	Yes	Yes
Literate FE	Yes	Yes	Yes	Yes	Yes
R^2	0.09464	0.10336	0.18176	0.14202	0.11958
Observations	567,530	405,781	523,369	523,369	523,369

Notes: Column 3 takes the inverse hyperbolic sine transformation of the occupation score as an approximation to the logarithm due to the occurrence of zero values. Column 4 indicates whether a son is self-employed, and Column 5 whether a son works in the wholesale & retail industry. It should be noted that observations in Column 2 are lower due to the absence of employment information for the year 1920. Standard errors are clustered at the industry-county level of the father and reported in parentheses. Estimates are weighted with inverse probability weights to control for potentially biased and unrepresentative samples due to census linking. See Section A.3 in the Appendix on how these weights are calculated. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table C.19 – Labor Market Effects Sons Older Cohort - Conditionally on being Employed in t+10

	asinh Occup. Score (1)	Self-Employed (2)	Wholesale & Retail (3)
$\Delta Refrig\times$ Ice Ind. Father $\times$ Post 1920	-0.0016 (0.0016)	-0.0002 (0.0013)	0.0011 (0.0020)
Year-County Father FE	Yes	Yes	Yes
Industry Father-Year-State Father FE	Yes	Yes	Yes
County Father-Industry Father FE	Yes	Yes	Yes
Literate Father FE	Yes	Yes	Yes
Age Bin Father FE	Yes	Yes	Yes
Citizen Father FE	Yes	Yes	Yes
Race Father FE	Yes	Yes	Yes
Married Father FE	Yes	Yes	Yes
Birthplace Father FE	Yes	Yes	Yes
Literate FE	Yes	Yes	Yes
R^2	0.20017	0.16932	0.14323
Observations	373,307	373,307	373,307

Notes: Column 1 takes the inverse hyperbolic sine transformation of the occupation score as an approximation to the logarithm due to the occurrence of zero values. Column 2 indicates whether a son is self-employed, and Column 3 whether a son works in the wholesale & retail industry. Standard errors are clustered at the industry-county level of the father and reported in parentheses. The sample only includes sons, who are employed in t+10. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.