

Consequences of Forced Labor Conscription: Evidence from Dutch Civilians*

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Abstract

While there is evidence of disruptions of labor market careers having a lasting effect, there is limited evidence on the long-term consequences of exposure to forced labor conscription, despite it being a frequent event in the previous century and still happening nowadays. I study the consequences of labor coercion for individuals' labor market outcomes. Cohorts of Dutch civilians faced a differential probability of labor coercion in Nazi Germany during WWII. Using Dutch census data from 1971 and Eurobarometer survey data from 1975 to 1994, I exploit the discontinuity in conscription at the date of birth to study the effects of conscription on long-term labor market success in a Regression Discontinuity Design. I find that conscripted individuals have lower education, income, and likelihood of employment. Studying heterogeneous effects, I find that facing harsher conditions in Germany are associated with lower labor force participation and worse health. My findings suggest that the negative impact on labor force participation is mitigated by being forced to work in sectors similar to those in the Netherlands.

Keywords: Labor Economic History, Coercive Labor Market, Forced Labor

JEL Codes: N34, N44, J24, J47

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1 Introduction

We know from previous literature that interruptions of a persons' labor market career can have lasting effects on their later economic success. One type of interruption that has not been studied is the exposure of forced labor policies. In today's economy, forced labor remains to be a large issue. According to estimates by the International Labor Office (ILO), around 27.6 million people worked in some type of forced labor in 2021 (ILO, 2022)¹. Given the high prevalence of forced labor, even today, it is important to understand the consequences such a disruption can have. This is inherently difficult in the contemporaneous setting for several reasons: First, data is often absent, and data collection could endanger affected workers (LeBaron, 2018). Additionally, the factors that contribute to the vulnerability of being exposed to forced labor may be correlated with the outcomes we are interested in (ILO, 2022). Moreover, current forced labor systems do not allow for studying long-term consequences.

I study the long-run consequences of facing labor coercion on individual labor market success, based on the historical system of forced labor set up by Germany during World War II (WWII). I exploit quasi-experimental variation in the assignment into forced labor for Dutch civilians to avoid endogeneity concerns. By combining archival data with micro-level census data I can circumvent the issue of data absence.

During WWII, there was a rising labor shortage in Germany which resulted from drafting men for military service and expanding the armaments industry. The German government thus filled this gap with civilians of occupied countries (Spoerer, 2001). In the Netherlands, the occupational regime decided to conscript all men born between 1922 and 1924 (aged 18–21 at the time) for labor in Germany in May 1943. The coercion was enforced through the withholding of food ration cards and forbidding businesses to employ men born in these years. At least 37% of these cohorts went to Germany for forced work. Anyone who was

¹Forced labor is defined as any work or service that is being extracted from a person under a threat of penalty, and for which the person has not offered themselves voluntarily ((ILO, 2022).

not granted an exception had to go into hiding². Assignment into sectors in Germany was done irrespective of previous skills. Most of the Dutch workers survived the forced labor experience and returned to the Netherlands after the end of the war (Tooze, 2006).

Exploiting the exogenous variation in being subject to conscription by the German forces based on birth date in the Dutch context, I compare later educational attainment, income, and likelihood of employment of individuals who were born within the years that were conscripted to that of individuals who were born before the conscripted years. More formally, I employ a regression discontinuity design at the cutoff of January 1, 1922 of the forced conscription policy³. I estimate an intention to treat effect, where the treatment of conscription into forced labor encompasses both the forced labor experience as well as the need to go into hiding to avoid transportation to Germany.

Using Dutch census data from 1971, when treated individuals were around 49 years old, I find that individuals born in the conscripted cohort have lower labor market success compared to those born before. They are 0.64%p. less likely to have finished secondary education, their yearly income is lower by 1% compared to the average income (or 2.1% of one standard deviation), and their likelihood of being employed is 0.68%p. lower, which translates to 2.9% of one standard deviation⁴. I find no differences in family formation, both for marital status as well as the probability of having children.

Since the treatment consists of either being forced to work in Germany or being forced to go into hiding, I link archival records of forced workers in Germany with the Dutch census data to construct a measure of the share of conscripted individuals who went to Germany to differentiate between the two treatment types⁵. I then allow for heterogeneous effects based

²Exceptions were granted to around 16% of the cohorts for men who were already working in industries that were strategic to the war effort.

³I focus on the lower cutoff date because the control group on the upper cutoff of 31.12.1924, individuals born in 1925, were the oldest cohort conscripted for the Indonesian War of Independence in 1946 with around 30% of the cohort being drafted (NIOD Inst. v. Oorlogs-, Holocaust- en Genocidestudies et al., 2022), thereby violating the assumption of nothing else changing at the cutoff

⁴The point estimate for income is -0.0289, where income is measured as yearly income in brackets of 4,000 Dutch guilder (2,916 EUR in 2024), meaning that on average the conscripted individuals' income is lower by 115 Dutch guilder (83 EUR in 2024).

⁵The data from the Arolsen Archives includes hand-transcribed records on the workers' name, place, and

on which type of treatment was more likely, forced labor or hiding. The effects are similar for both, implying that the treatment effect is driven the disruption of the labor market career, independent of whether that constituted being forced to work or being forced to go into hiding.

Exploiting information on forced workers' location in Germany from the archival records, I show that the negative effects on later labor market success are most pronounced for individuals who had a higher exposure to severe living conditions. I proxy the severity of the forced labor experience in Germany by the share of houses damaged due to bombings and the distance to so-called labor re-education camps which served as punishment for forced workers. I then calculate the average weighted exposure to severe conditions for forced workers from each Dutch municipality. I find that the lower probability of being employed is driven solely by conscripted individuals who were exposed to more severe conditions in Germany. I then directly study the effects of the treatment on physical and mental health. I find that the likelihood of needing assistance in daily life in 1971 is higher for conscripted individuals from places with higher exposure to severe conditions. I also find suggestive evidence for lower subjective life satisfaction for individuals from the conscripted cohort using Eurobarometer survey data covering the period from 1975 to 1994, both pointing to adverse health effects as a possible mechanism for the lower labor force participation.

I find that the loss in relevant labor market experience due to forced labor is also a relevant factor, by showing that the negative effect on labor force participation is mitigated for individuals who were being forced to work in sectors similar to the ones in a persons' place of origin. This suggests that the loss of relevant labor market experience was less severe if individuals could continue working in the sectors that they were forced to work in while in Germany. Specifically, I split the sample by how similar the employment shares in the average German county a person was exposed to are compared to the employment shares

date of birth, and their location in Germany. I cleaned the hand-transcribed places of birth to match the Dutch municipalities in the census data, and classify an individual's gender using their first name and name frequencies from Meertens Instituut (nd). I link the data based on gender, date of birth, and place of birth.

in their municipality of birth. The negative effects conscription on labor force participation are driven completely by individuals who were forced to work in sectors different from the sectors at their municipality of birth, which could be due to gaining less valuable labor market experience in their forced labor experience.

The results are robust to several robustness checks, including different specifications of the RDD equation, the use of different bandwidths, and the inclusion of individuals of the Dutch Hunger Winter regions. Additionally, I estimate placebo estimates with the cutoff at different years, showing that there are no significant differences in labor market success at these cutoffs.

My results show important consequences of the disruption of the forced labor conscription. Yet, they still only constitute the lower bound of the social costs of forced labor conscription in a more generalised sense because the Dutch civilians were treated relatively better than forced workers of other nationalities. This was also mirrored by German policymakers when deciding on compensation for affected former forced workers in the early 2000s, as they excluded Western forced workers, including the Dutch ones, due to a lack of discriminatory living conditions (Stiftung Erinnerung, Verantwortung und Zukunft, 2017). My findings contradict this assessment, showing that especially those Dutch forced workers who faced more severe conditions in Germany did suffer from long-lasting effects on their labor market success and their health.

My paper contributes to several strands of literature on different types of disruptions of a person's labor market career. Most related are studies looking at conscription into the army (Angrist, 1990; Blattman and Annan, 2010; Imbens and Klaauw, 1995). I contribute to this literature by studying conscription into other sectors than the military. The exogenous assignment of forced workers into sectors and locations in Germany allows me to identify which parts of the forced labor experience drives the effects. Moreover, by combining archival records with micro-level census data, I can construct estimates for the extend to which conscripted individuals went into hiding, which is usually hard to measure. This allows me to

study how an involuntary absence from the labor market affects an individuals' labor market success, related to previous papers on work displacement due to plant closures (Huttunen et al., 2011; Ichino et al., 2017).

This paper also contributes to the literature on forced migration by studying a setting where forced migrants were able to return to their home country, which allows to study the effects of temporary displacement, and excludes that effects are driven by the ongoing exposure to conditions in the destination location (Bauer et al., 2013; Bauer et al., 2019; Becker et al., 2020; Becker, 2022; Sarvimäki et al., 2022).

More broadly, this paper is also related to the literature on consequences for labor market outcomes of facing other adverse events, such as natural disasters (Deryugina et al., 2018; Schwank, 2024), war (Braun and Stuhler, 2023; Kesternich et al., 2014) and hunger (Ramirez and Haas, 2022).

By studying the consequences of forced labor on an individual level, my paper also directly contributes to the literature on forced labor. Previous studies have compared regions with more or less intensive use of labor coercion and show persistent negative effects (Bertocchi and Dimico, 2014; Buggle and Nafziger, 2021; Buonanno and Vargas, 2019; Cinnirella and Hornung, 2016; Dell, 2010; Fujiwaray et al., 2017; Mitchener and McLean, 2003; Nunn, 2008; Soares et al., 2012; Markevich and Zhuravskaya, 2018). Persistence is thus often driven by the institutions that were shaped by the forced labor systems. In the case of Dutch civilians being coerced into labor in Germany, both the group intended for the treatment and the control group live under the same institutions in the Netherlands after the end of WWII, but only differ in their exposure to forced labor conscription. I can therefore separate the effects of forced labor conscription for individuals from the effect of forced labor systems on institutions.

As the conscripted individuals were around 21 years old at the onset of the forced labor policy, my study also contributes to the literature on the consequences of labor market conditions at early stages of a persons' labor market career (Oreopoulos et al., 2012; Schwandt

and von Wachter, 2020; von Wachter, 2020). I contribute to this literature by showing that both an involuntary absence from the labor market due to hiding, as well as labor market experience in sectors that a person did not freely chose and that is not relevant for their later labor market career have a long-lasting effect on later labor success.

Finally, my paper also adds to the literature on the forced labor regime by Germany during WWII by being the first one to empirically evaluate the long-term consequences for workers after WWII had ended and the forced labor regime was abolished. While there is ample research on it from a historical perspective (Herbert, 1999; Pfahlmann, 1968; Homze, 1967; Sijes, 1966; Spoerer, 2001; Spoerer and Fleischhacker, 2002), its economic aspects, and specifically the consequences of forced labor for individuals' labor market success, have not been studied before.

2 Historical Background

During WWII, the German economy faced an intense labor shortage due to the expansion of the armaments industry and the drafting of men for fighting at the front. Replacing the missing men with women was an unpopular policy because it went against the Nazi ideology of women's roles as housewives and mothers. The *Reichsarbeitsministerium* (Ministry of Labor) therefore set out to recruit civilians of occupied countries, first by advertising to unemployed workers, and later by using coercion (Spoerer, 2001). Since it was more efficient to produce in Germany than in the occupied countries, most of these civilians were transported to Germany to work there (Tooze, 2006).

In the Netherlands, the occupying regime announced in May 1943 that they would conscript all men of specific age groups for work in Germany (the so-called *Yearclass Action*). In June 1943, the cohort of men born in 1924 was the first to be transported to Germany, and in August the cohorts of 1923 and 1922 followed. The Yearclass Action was initially scheduled to include all men born between 1908 and 1925, but due to concerns of turmoil

in the Dutch population because of the unpopularity of the conscription of age groups, the other birth cohorts were ultimately not called upon for forced labor. Coercion was executed by withholding food ration cards and forbidding firms to employ men from these cohorts.

In total, at least 77,200 Dutch forced workers born between 1922 and 1924 were recorded in Germany during WWII in the data by the Arolsen Archives. Comparing that to a total of around 210,500 men born in these years according to the 1971 census, compliance was at least around 37%. Men already working in war-related industries were granted exemptions, which applied to 16% for those born in 1922, 19% for those born in 1923, and 17% for those born in 1924 (hsv, 1943; Sijes, 1966). The remaining men went into hiding with the help of the resistance, who forged food ration cards and helped with the placement of men of the conscripted age groups into hiding locations using false documents (Sijes, 1966; Warmbrunn, 1972). The situations in hiding varied, but often men hid in locations away from their homes, with limited contact to their social networks to avoid being found (Warmbrunn, 1972). Figure 3 shows the exogenous variation that I use in this study: Men from the conscripted cohort were more likely to be forced to work in Germany than men born before the cutoff, and only men from the conscripted cohort were forced to systematically go into hiding until the end of the war to avoid the forced labor⁶.

The conscripted individuals who were taken to Germany were distributed irrespective of their skills or previous training and over large parts of Germany. Figure ?? shows the regional distribution of Dutch male forced workers born in the conscripted years 1922–1924 over the German counties. The men were assigned quasi-randomly into the specific locations and industries, based on local labor shortages at the time of their deportation that companies reported to their local *Arbeitsamt* (employment office). The administrative effort of recording and assignment based on previous skills and training was deemed too costly (Kuck, 2010; Marx, 2019). The majority of the Dutch forced workers were employed in manufacturing

⁶The numbers of forced workers is derived by comparing the sample size in the Arolsen archival records to the sample size in the census data 1971. The share of men who went into hiding is derived by subtracting the number on the share of men who were granted an exception taken from German records from 1943, which is available separately for each cohort.

and construction⁷, and the pay was lower than that for German workers (Herbert, 1999; Sijes, 1966; Tooze, 2006).

The living conditions varied widely, as firms were responsible for housing and feeding the forced workers (Althausen, 1999). Most Dutch workers were housed together in barrack camps or repurposed public buildings. Food supply and nutrition was often of low quality, the access to medical care was scarce or non-existent, and both deteriorated as the bombing of the allied forces intensified. Forced workers were also tasked with clean-up after bombing attacks (Sijes, 1966). In case of any so-called nondisciplinary conduct such as sabotage or absenteeism, forced workers were sentenced to stays in so-called *Arbeitserziehungslager* (labor education camps) for several weeks, where conditions were similar to those in concentration camps (Lofti, 2000). While the forced workers were mostly promised yearly contracts at deportation, the majority of workers were not allowed to leave after that period and had to stay until the end of the war (Beening, 2003). When workers tried to flee to return to the Netherlands, they faced being sent to labor education camps and then being brought back to Germany upon being captured (Kuck, 2010).

The estimates on deaths of Dutch forced workers in Germany range from 5,000 to 29,000, meaning that based on the total estimated number of Dutch forced workers of somewhere between 450,000 and 530,000, between 93% and 99% survived the coercion (Beening, 2003; CBS, 1947; Spoerer, 2001; Warmbrunn, 1972). After the successive liberation of Germany in 1945, the Allied Forces organized the transports of former forced workers back to their home countries. By September 1945, 98% of all Dutch persons present in Germany at the end of the war had returned to the Netherlands (Grüter and Mourik, 2020; Proudfoot, 1957). At their return, the forced workers faced stigma because their labor for Germany was seen as collaboration with the enemy. Therefore, most of them stayed silent about what happened to them during the war. Only in the 1980s, a public debate about the experiences of the forced labors began in the Netherlands (Kuck (2010))⁸.

⁷Figure 13 in the appendix shows the number of forced workers in different industries.

⁸The first book interviewing former forced workers about their experiences was published in April of

The control group to which I compare the experiences of the individuals subject to the forced labor conscription was also affected by the experience of living through WWII in an occupied country, and this may have affected their labor market prospects as well. However, the Dutch economy was doing comparatively well: In 1945, the Dutch GDP was 86% of that of 1938, and industrial capacity in 1945 was larger than before the war (Lak (2016)). Both the treatment and the control group were exposed to the war. Secondary education typically finished at nineteen years old, so the individuals around the cutoff of January 1, 1922 should have completed all schooling but university already by the start of the Yearclass action in May 1943 (Warmbrunn, 1972). In 1940, only 4% percent attended higher education, and universities mostly stopped operating from 1943 onwards, so neither the control nor the treatment group would have had significant higher education during the period of conscription until the end of the war in 1945 (Van Eden, 1946; Warmbrunn, 1972).

One experience that only the control group faced which may affect later labor market outcomes is the Dutch hunger winter, which took place between November 1944 and May 1945 in urban regions in the West (de Zwarte, 2020). While the groups that suffered the most directly were infants and older people, Ramirez and Haas (2022) show that there are negative effects on education for adolescents of up to 14 years old (which is when their sample ends). I therefore exclude individuals from areas affected by the hunger winter in my baseline sample to abstract from any possible differences driven by the hunger experience⁹.

There was no systematic large-scale enlisting of men into the *Wehrmacht* that differed for age-groups¹⁰. For the Indonesian War of Independence (1949–1949), the cohorts of 1925, 1926 and 1927 were conscripted (NIOD Inst. v. Oorlogs-, Holocaust- en Genocidestudies et al., 2022)¹¹. Thus, at the upper cutoff of the forced labor conscription cohort window

2024 (?)

⁹Also men who went into hiding were probably less affected by the hunger winter, as most hiding locations were rural areas (Warmbrunn, 1972)

¹⁰Military conscription for the Dutch armed forces came to a halt with the capitulation of the Netherlands in May 1940 (Jongbloed, 1996). Around 40,000 men were conscripted into building coastal defense constructions in 1944, but not based on their date of birth (Sijes, 1966)

¹¹In total, around 100,000 conscripted solidiers were drafted (NIOD Inst. v. Oorlogs-, Holocaust- en Genocidestudies et al., 2022). The cohort size of these three years of birth is around 200,000, so around half

(31.12.1924), the conscription for the Indonesian War of Independence is a factor that only affected the possible control group, making it impossible to identify the effects of forced labor conscription during WWII as conscription for military service also affects labor market success (Angrist et al., 2010; Blattman and Annan, 2010; Hjalmarsson and Lindquist, 2019). The cutoff for school enrollment was in summer (Richardson, 2000).

In 2000, the German government set up a fund to pay symbolic amounts of compensation to former forced workers of the occupied countries, following pressure due to impending law suits of former forced workers against German companies located in the United States. Depending on the severity of the treatment, individuals were paid between 572 EUR and 7,760 EUR (629 USD to 8,546 USD). Individuals who were deported and had to work in manufacturing were paid 2,560 EUR (2819 USD) as a recognition of the the harsher conditions compared to those working in the agricultural sector. However, because of the limited sum of the compensation program and because of the lower severity of their experience and a “lack of deportation and discriminating living conditions”, forced workers from Western countries were excluded from this compensation program unless they had been working in a concentration camp or other comparable places of detainment (Stiftung Erinnerung, Verantwortung und Zukunft, 2017). Thus, only 4,500 Dutch individuals received a compensation through this program, despite the fact that the majority of the around 500,000 Dutch civilian workers were involuntarily deported from the Netherlands, and the majority of them worked in the industry sector (77% according to Herbert (1999)).

3 Data

3.1 Dutch Census Data

To estimate the consequences of being conscripted into this forced labor system, I individual-level admin data from the 1971 census (*14de Algemene Volkstelling*) which is a comprehensive

of these men were drafted.

census of the Dutch population¹². To identify treatment and control group, I use the individuals' gender, month of birth, and year of birth. The treatment group is defined as all men born in 1922, 1923 and 1924. The control group are individuals born in the three years prior to the conscription, so 1921, 1920 and 1919. The individuals are thus between 46 and 52 years old at the time of the census.

The outcomes to measure labor market success that I use are a dummy variable for finishing secondary education, labor income (reported in 6 different income brackets with a range of 4,000 Dutch guilder (1,815 EUR or 2000 USD)), and a dummy variable of whether a person is employed. I also use the marital status and a dummy for whether an individual has children as a proxy for their social situation, and a person's need for assistance in everyday life as a proxy for their health. Table 1 shows the descriptive statistics of these variables¹³¹⁴.

The 1971 Census does not include the municipality of birth directly, but only the current municipality and an indicator for whether an individual still lives in their municipality of birth (excluding temporary absences such as war-related reasons). I therefore only know the place of birth for non-movers (199,797 from the total 411,192 of the three-years sample). I exclude individuals born in the municipalities that were affected by the Dutch Hunger Winter following Conti et al. (2024)¹⁵. The sample then includes 356,681 observations. When merging further data sources based on the place of birth, I further restrict my analysis to individuals who did not move. This reduces my sample to 145,286 observations.

3.2 Individual Archival Records

To disentangle the bundled treatment of being forced to work in Germany and being forced to go into hiding, and to investigate heterogeneities based on the forced labor experience in Germany, I supplement the data with archival records on forced workers during WWII

¹²The non-response rate was 0.2%

¹³The sample is based on the median optimal bandwidth of 15 months.

¹⁴The non-response rates are around 17% for educational attainment and 7% for income, but these numbers are similar for treatment and control group, see table 1.

¹⁵These municipalities are Amsterdam, Delft, The Hague, Haarlem, Leiden, Rotterdam and Utrecht.

provided by the Arolsen Archives. The archive evolved from the International Tracing Service (ITS) established by the Allied forces, and its aim is to document and trace victims of the Nazi regime. The majority of the data originates from registration efforts by the Allied forces after WWII to organize the transport of the displaced persons back to their country of origin. I use data on so-called displaced persons, who are defined as individuals who had been deported by the Nazi regime (Höschler and Panek, 2019). While these do include prisoners of war and former inmates of concentration camps, the vast majority of them are forced workers¹⁶. The number of total unique Dutch individuals in the archival data of around 473,000 also matches the historical estimates of Dutch forced workers of somewhere between 450,000 and 530,000 (CBS, 1947; Spoerer, 2001). I therefore will assume that all individuals in this dataset are forced workers. Considering that some forced workers fled or were allowed to leave before the end of the war and are therefore missing from the records, this should not bias my results significantly.

The data includes information on the full name, date of birth, location of birth, and the location where the person stayed in Germany. The original sample consists of 594,967 observations. Some individuals may show up more than once in the data because multiple sources have been aggregated for the archival records. I therefore use a fuzzy linkage method to link duplicate entries of the same person to one another and exclude the double-counting of individuals. I follow Abramitzky et al. (2021) and adjust their algorithm slightly to exploit the data structure of the archival records¹⁷. This reduces my sample to 473,406 individuals.

Since the archival data does not include the gender of the individuals, I use the data on first names and combine this with information on name frequency based on gender from the Corpus of First Names in the Netherlands published by the Meertens Instituut to classify individuals as male or female (Meertens Instituut, nd)¹⁸. For the relevant cohorts of 1922–

¹⁶One estimate taken from a statistic on Dutch individuals returning from Germany at the end of the war put the share of forced workers of all Dutch individuals who returned after WWII at 92.5%, while the prisoners of war make up another 3.6%, and inmates of concentration camps make up 3.9% (Lagrou, 1999)

¹⁷See section 5.1.1 for a detailed description of my approach

¹⁸See section 5.1.1 for a detailed description of my approach.

1924, there are 84.2% male and 10.7% female individuals¹⁹. I restrict the sample to unique male individuals from the cohorts of 1922, 1923 and 1924, which reduces the number of observations to 72,898 observations.

I link the archival records to the census data using the place of birth²⁰. This information is available for 40.1% of the sample. I employ a fuzzy merge complemented with manually coded municipalities²¹. The final sample consists of 24,151 observations that I am able to link to the census data²².

Comparing the sample size of each municipality and each month of birth, I calculate the average share of conscripted individuals who were deported to Germany²³.

3.3 Eurobarometer

To investigate effects on mental health, I use Eurobarometer survey data which includes a question on self-reported life satisfaction. The Eurobarometer is a survey done in all member countries of the European Union and samples 1,000 random individuals per country in every survey round. I use all Eurobarometer survey waves since 1975, when age was first recorded, until 1994, when the youngest individuals in the potential treatment group would be 70 years old (Kommission Der Europäischen Gemeinschaften, 2012)²⁴. Since I only know an individuals' age and not their exact date of birth, I restrict the analysis to individuals for whom I know for certain that they are in the control or treatment cohort²⁵.

To validate my findings from the census data, I repeat the analysis on economic outcomes

¹⁹For the remaining 5.1%, I was unable to assign a gender based on their first name.

²⁰A linking on an individual level is not possible, since the 1971 Census does not include information on the name and exact date of birth

²¹See section 5.1.1 for a detailed description of my method.

²²I was thus able to link 82.6% of all observations which have information on their place of birth

²³In cases where the number of forced workers in the archival records is larger than the number in the census, I restrict the compliance measure to one.

²⁴This includes waves three through 42 and amounts to 50 waves in total.

²⁵To give an example of an individual with an uncertain treatment status, imagine a person who reports to be 53 years old at the time of the third Eurobarometer survey of June 1975. They were thus born between June 1921 and June 1922 and could be part of the treatment cohort (born 1922) or the control cohort (born 1921).

available in the Eurobarometer data²⁶. The outcome on mental health is subjective life satisfaction (ranging from 0 to 3)²⁷. Table 4 shows the descriptive statistics of the variables of interest.

3.4 Forced Labor Experience

To study heterogeneities based on the type of forced labor experience that individuals faced, I add data on exposure to severe conditions in Germany, and data on the industry structure in Germany and the Netherlands to the data.

3.4.1 Exposure to severe conditions

I proxy severe conditions in Germany by two measures, exposure to war and distance to so-called labor education camps, to which forced labor were sentenced in case of disobedience. The intuition is that forced workers suffered most in areas with lots of bombings, as shelters were often reserved for German citizens and they were often forced to clean up after the bombings. It is also plausible that forced workers faced a higher probability to be sent to a labor education camp if one was close-by, as these stays were temporary and the forced workers were supposed to return to their former occupation after the sentence ended. The data on war exposure comes from Peters (2022) and measures the share of houses damaged during the war by Allied bombings. This data is available for West Germany, where also the majority of Dutch forced workers were located (see figure 1). The locations of labor education camps come from a map by Lofti (2000) which I geocoded. Both variables are then aggregated to the level of Dutch municipalities by calculating the weighted average over all German counties, using the number of male conscripted forced workers present in these counties as the weights.

²⁶These are years of education (ranging from 7 to 15), income class (ranging from 1 to 12 with brackets of typically 250 Dutch guilder (114 EUR or 125 USD)) and a dummy for whether a person is employed

²⁷The exact wording of the question for life satisfaction is “Taking all things together, how would you say things are these days - would you say you’re very happy, fairly happy, or not too happy these days?”

3.4.2 Industry Structure

I proxy the industry in which forced workers were employed by the employment shares in German counties in which the forced workers were present using the 1939 occupational census (Braun and Franke, 2021). The underlying assumptions are that the industry structure of 1939 is similar to that of 1943–1945, when the Dutch forced workers were present in Germany, and that the forced workers were distributed across industries according to the industry composition of the county to which they were deported to. I then link this data to the 1971 Census by again calculating the weighted average based on where forced workers from these municipalities were located in Germany.

To investigate whether the effects on labor market success and occupational choice differ depending on how different the industry composition was at the German county during the forced labor stay compared to the setting from where individuals originally come from, I use data from the Beroepstelling 1930 (CBS, 1934) to measure the employment shares at the location of origin. Due to lack of individual-level data of occupation before the war, I again have to assume that the likelihood of an individual working in a specific industry is according to the industry composition in their municipality of birth.

4 Empirical Strategy and Results

4.1 Labor Market Outcomes

4.1.1 Empirical Strategy

The challenge when identifying causal effects of forced labor experiences on later labor market outcomes is to find a suitable control group, which could have also been subject to the forced labor, but, for reasons exogenous to their labor market performance, did not share this experience of being forced to work in an employment that they did not chose for themselves. Typically, especially vulnerable groups of people are faced with coercion of some kind to

enter such a forced labor “employment” (ILO, 2022), and this vulnerability could possibly translate into different labor market outcomes compared to people who were able to evade the coercion, regardless of the forced labor experience. Using the historical setting of the forced labor regime in WWII as a natural experiment allows me to avoid this endogeneity concern. While all years of the cohorts of 1908–1925 were considered for conscription through the Yearclass action, only the cohorts of 1922–1924 were actually drafted. Thus, individuals born before the cutoff of January 1, 1922 pose a suitable control group since the reason that they were not drafted was not due to differences in any underlying characteristics that may also affect labor market outcomes, as they were deemed as suitable for forced labor as the actually drafted cohorts.

I exploit the exogenous assignment into forced labor based on an individuals’ year of birth by using a fuzzy Regression Discontinuity Design (RDD) and compare individuals born just within the conscription period to those born just outside of the conscription period. The identifying assumption is that individuals born after January 1st are similar to those born before, and labor market success would be smooth in the absence of treatment²⁸

The identifying assumption of RDD relies on the fact that there are no other discrete changes at the cutoff of forced labor recruitment which could potentially affect labor market success (Cattaneo et al., 2019). To the best of my knowledge, there were no other policies that changed discontinuously at the cutoff dates of the conscription policy (January 1, 1922). The cutoff for school enrollment was mid-year (Richardson, 2000) and the limited conscription into military during WWII was not based on age (Sijes, 1966). The oldest cohort conscripted for the Indonesian War of Independence was 1925 (NIOD Inst. v. Oorlogs-, Holocaust- en Genocidestudies et al., 2022)²⁹. Both treatment and control group were subject to the war,

²⁸I thus rely on a continuity based identification. The alternative of Local Randomization relies on the assumption that potential outcomes are unrelated to the running variable, which is violated because of age effects, since age is related to a persons labor market success. Using a discrete running variable such as month of birth in the continuity-based RDD is appropriate if the number of mass points is sufficiently large (Cattaneo et al., 2024). Since my potential treatment window is three years, this assumption is satisfied.

²⁹Lacking pre-treatment individual level data, I cannot check for continuity at the cutoff of labor market outcomes prior to the treatment. Outcomes available in the census might also have been affected by labor conscription.

but only the control group would have experienced the Dutch Hunger Winter in 1944–1945. I therefore exclude men from municipalities affected by the Hunger Winter.

Another identifying assumption of RDD is that individuals cannot manipulate the running variable. While a persons’ date of birth is generally exogenous, it is possible that individuals may have forged their birth certificates to evade treatment and thereby sort into the control group, and the motivation for this manipulation may also be correlated with underlying characteristics that affect an individuals’ later labor market trajectory. For this to bias my results, individuals would have to still use the documents with their incorrect date of birth in 1971. As the incentive to lie about their date of birth ceased after the end of WWII, this is unlikely. Figure 2 depicts the density of month of birth in the 1971 census. The distribution is flat and there seems to be no discontinuous bunching left and right of the conscription period. This also alleviates concerns on differential survival probability of treatment and control group and thus sample selection issues, as at least at the time of measurement for labor market success in 1971 (when treated individuals were aged around 49 years old), there are no differences in the amount of individuals in either group visible.

If these assumptions are fulfilled, then any difference at the cutoff can be attributed to the treatment effect. In my setting, the treatment of forced labor conscription is a bundle of different experiences: For individuals who were deported to Germany it entails being forcibly moved to another country, then being forced to work in an occupation that is not freely chosen, possibly being subject to harsh living conditions and punishments, and having to hide this traumatic experience due to the associated stigma. In the case of those who went into hiding, the treatment consists of having to leave their known environment, living in fear of being found, and often having no formal employment (Warmbrunn, 1972)³⁰.

Some individuals born within the conscripted years were granted an exemption and had to endure neither forced labor nor going into hiding, and some individuals born outside of these years still faced forced labor because they were coerced through other measures than

³⁰See section 2 for a detailed discussion of both experiences.

the Yearclass action. So there are non-compliers with the treatment assignment in both the control and the treatment group. I estimate a reduced form of a Fuzzy RDD, where I exploit that the probability of treatment discontinuously changes at the cutoff of conscription, using the Dutch census of 1971. The estimation equation takes the following form:

$$Y_i = \beta_0 + \beta_1 1\{MonthofBirth_i \geq c\} + \beta_2 MonthofBirth_i + \beta_3 MonthofBirth_i^2 + \epsilon_i \quad (1)$$

Y_i are labor market outcomes, specifically educational attainment, income class, employment status, and occupational rank, which measures the type of position a person has if employed. $MonthofBirth_i$ is the running variable and c is the cutoff (January 1, 1922). $1\{MonthofBirth_i \geq c\}$ is the indicator for treatment, which is one for treated individuals and zero for the control group. The coefficient β_1 is the intention to treat (ITT) effect, which is the effect of being subject to conscription into forced labor, irrespective of actual compliance, compared to individuals who were born outside the conscripted years and were thus less likely to face forced labor or going into hiding. This effect is thus a lower bound of the true effect of being subject to forced labor conscription as the control group includes individuals also affected by forced labor, and the treatment group includes individuals who were able to avoid forced labor and going into hiding. I include a linear and a quadratic term of the running variable $MonthofBirth_i$ following Gelman and Imbens (2019)³¹. I a bandwidth of 15 months, which is the median of the optimal bandwidths from all labor market outcomes, based on the MSE-optimal bandwidth selection and a triangular kernel as suggested by Cattaneo et al. (2019)³².

³¹I perform robustness checks using only a polynomial of one of the running variable and including an interaction term of the running variable and the treatment indicator $1\{MonthofBirth_i \geq c\}$, see figure 9.

³²I perform robustness checks using different bandwidths and uniform kernel, see figure 9

4.1.2 Results

Figure 4 shows the average outcomes for each month of birth and the corresponding function estimated using equation (1), with a bandwidth of 15 months³³. I find that the highest educational attainment (measured from 0 to 8) is lower by 0.041 levels, which corresponds to 2.4% of one standard deviation. The income class is lower by 0.0289 levels, which corresponds to 2.1% of one standard deviation. Since the income is classified into bins of 4,000 Dutch guilder (1,815 EUR or 2000 USD) and measured as yearly labor income, this implies the forced labor conscription lowers the yearly labor income by 115 Dutch guilder (52 EUR in 2002 or 83 EUR in 2024). Compared to the average income, this is a reduction of 1% of the mean. The effect on the likelihood to be employed is -0.68%p, which is 2.9% of the standard deviation. I find no differences in an individual’s occupational rank if employed, implying that the type of position that individuals hold once they do enter the labor force do not differ significantly.

The results are robust to a number of different specifications. Figure 9 shows the estimates for regressions different specifications of the RDD equation: Using only a polynomial of one for the running variable $MonthofBirth_i$, including an interaction term of the running variable and the treatment indicator $1\{MonthofBirth_i \geq c\}$ to allow for different slopes on both sides of the cutoff, using different bandwidths (half and double of the optimal bandwidth), using a uniform kernel, running a Poisson regression for outcomes that are count variables, and including individuals from the Hunger Winter regions.

I also estimate placebo specifications, shifting cutoff to years where nothing should have changed at January 1st that affects labor market success. Figure 10 shows the results for four different placebo cutoffs, which are all insignificant for educational attainment, income class and employment status³⁴.

The effects which I estimate are likely a conservative lower bound of the persistent effects

³³The underlying regression results are shown in table 2

³⁴I used cutoffs where the three years on both sides of the cutoff only include the control group and again took the median optimal bandwidth.

of forced labor. While the treatment and control group are comparable in the sense that both experienced the war, and I exclude individuals from regions affected by the Dutch Hunger Winter, other war-related factors that only the control group experienced could still lead to an underestimation of effect sizes³⁵. Moreover, because the Dutch forced workers were treated relatively better than forced workers of other nationalities, the effects for forced workers of other occupied countries would probably be larger than for those of Dutch civilians.

4.2 Family Formation

So far, I have looked at the effects of forced labor conscription on a persons' labor market success. To understand what consequences the conscription into forced labor has on the individuals' social life outside of their labor market experience, I look at marital status and parental status, meaning the probability to have children.

Figure 7 shows the average likelihood to be married and to have children as reported in the Dutch census of 1971 in a 15 month bandwidth around the cutoff, and the results from equation (1)³⁶. There is no discontinuous difference between the treatment and control group at the cutoff for both marital status and the probability to have children, meaning that at the time of the census, when individuals were aged around 49 years old, forced labor conscription does not seem to affect family formation.³⁷ Figure 8 confirms these results also for later stages in life using the Eurobarometer data, estimating equation (2) with marital status and parental status as outcome variables.

³⁵The Dutch Hunger Winter took place in the winter of 1944-1945 when the forced workers were still in Germany and affected only the urban regions in the west

³⁶Marital Status is a dummy that takes the value of one for ever being married (including widowed, living separately and divorced), and zero otherwise

³⁷Table 3 shows the full regression results.

4.3 Mechanisms

4.3.1 Forced Labor and Hiding

Until now, I estimated the intention to treat effect, where the treatment is a bundle of being forced to work in Germany and being forced to go into hiding. To disentangle between these two factors, I conduct a heterogeneity analysis based on the share of conscripted individuals from each Dutch municipality that can be found in the archival records. Since the ability and probability to go into hiding may be in part driven by factors that could also affect labor market outcomes, the results are suggestive evidence and should not be interpreted causally³⁸.

The 1971 Census does not include the municipality of birth itself, but only the current municipality and an indicator for whether an individual still lives in their municipality of birth (excluding temporary absences such as war-related reasons). I therefore first restrict the census data to non-movers which leaves me with 62,319 observations in the sample with a 15 month bandwidth.

For each Dutch municipality, I then compared the sample size of men born in the respective municipality and within the treatment group to the numbers of men from that date and place of birth who show up in the cleaned and linked data by the Arolsen Archives on forced workers in Germany. Because I was only able to link a subset of individuals, this number is a lower bound of the actual share of men who were deported to Germany from each municipality. Figure ADD FIGURE shows the regional distribution of the share of deported conscripted men over the Dutch municipalities.

I then split the sample by municipalities with a deportation share above and below median³⁹ and repeat the analysis for labor market outcomes by estimating equation (1) first for the new baseline of non-movers and then separately for each sample. The results are displayed in figure 11a. In this new baseline, the effects for education and income become

³⁸For example, men from families that were better connected may have had an easier time to go into hiding, and this network may also be beneficial for landing high-paying jobs.

³⁹The median share of deported conscripted men is ADD NUMBER

insignificant and close to zero, while the effect on employment probability is still negative and significant.

The effects are similar for both groups, suggesting that the negative effect of treatment comes from both going into hiding and from the forced labor experience itself. Though insignificant, the results suggest that individuals from municipalities that went to Germany at a higher rate tend to hold slightly more skilled occupations, while the effect is negative for individuals who went into hiding at a higher rate, pointing to some skill acquisition during the forced labor experience.

4.3.2 Exposure to severe conditions

To open up the black box of the forced labor experience, I conduct a heterogeneity analysis based on severity of the forced labor experience in Germany to understand whether being exposed to harsher circumstances during the forced labor period may be a contributing factor for the negative effects on labor market success. Since allocation to locations in Germany was done based on ad-hoc demand for labor, the exposure to different conditions is as good as random. I can thus use information on the location of forced workers in Germany from the archival records to exogenously proxy for variation in the severity of the forced labor experience.

Using information on the share of houses damaged due to bombings and the distance to so-called labor education camps, to which forced workers were sent in case of disobedience, I construct a measure of average weighted severity of the forced labor experience that individuals from for each Dutch municipality faced. As shelters were often reserved for Germans, and living conditions for forced workers deteriorated with more severe Allied bombings (Sijes, 1966), it is likely that forced workers in areas with a high number of Allied bombings suffered more. The likelihood to be sentenced to a (temporary) stay at a labor education camp was probably also higher for individuals in counties close to the next such camp. Figure ADD FIGURE shows the regional distribution of both measures of severe

conditions over the Dutch municipalities.

I again split the sample based on whether an individual is from a municipality with an above or below median exposure to severe conditions⁴⁰. Figure 11b shows the results for the sample split by the average weighted share of houses damaged, and figure 11c shows the results for the split by average weighted distance to the nearest labor education camp. Since the regional distribution of forced workers in Germany was arguably exogenous (see section 2 for a detailed discussion), the differences in exposure to severe conditions should also be as good as randomly assigned.

The lower probability of being employed is driven solely by individuals from Dutch municipalities where forced workers were more exposed to more severe conditions in Germany (both for the share of houses damaged and the distance to labor education camps). This points to adverse health effects as a possible contributing factor for the long-lasting lower labor force participation.

To test if indeed poorer health due to harsher forced labor conditions is a driving mechanism for the lower likelihood of employment, I repeat the heterogeneity analysis with a direct measure of an individual's health. I use the question of whether an individual is in need of assistance by others for their own care, household tasks, or for getting to places outside of their home as a proxy for health⁴¹. I find that individuals exposed to more severe conditions have a higher likelihood to need assistance, which is in line with the interpretation that a severe forced labor experience led to worse health, which in turn can be one explanation for the lower labor force participation of treated individuals.

To not only look at physical health but also at mental health as a possible contributing factor, I turn to the Eurobarometer data to study the effect of forced labor on life satisfaction. As this data does not contain an individual's month of birth nor place of birth, I can only estimate a simple difference equation of the intention to treat effect, without any het-

⁴⁰The median average weighted share of houses damaged in Germany is ADD NUMBER, and the median average weighted distance to a labor education camp is ADD NUMBER.

⁴¹Note that not needing help and not answering the question is both coded the same, so the results have to be interpreted with caution.

erogeneities by the severity of the forced labor experience⁴²⁴³. Figure 6 suggests that while the effect does not reach significance, there may be a negative effect on life satisfaction for treated individuals, further XX that poorer health, both physical and mental, may be one reason for the negative effects on labor market success. This interpretation is also supported by a survey of dutch men born between 1920 to 1929 conducted in 1995, which found that the likelihood for PTSD is positively correlated with the likelihood of having been a forced worker during the war (Bramsen, 1998)⁴⁴.

4.3.3 Industry Structure

Because the assignment into occupations in Germany was done irrespective of prior skills and training, but only based on local labor shortages at the time of deportation, the forced labor experience can also be thought of as a random assignment into a specific industry. I therefore want to understand whether the human capital acquired in certain industries during the forced labor experience may have played a role in shaping later labor market success.

I conduct a heterogeneity analysis based on whether the type of industries to which forced workers were exposed to in Germany differed from the industries present in their home municipalities. Specifically, I identify the industry sectors which pay above the median of all sectors in 1971, and then calculate the employment share in these high-paying industries for both the German counties and the Dutch municipalities based on employment censuses from the 1930s. I then assign each Dutch municipality the average employment share in high-paying industries to which the forced workers were exposed to in Germany, again weighted by the number of conscripted forced workers who went to each German county. The underlying assumption here is that individuals were more likely to be employed in a specific sector if it

⁴²I estimate the following equation: (2) with a measure of life satisfaction as the dependent variable which I harmonized to a scale from zero to three. Using only the age as the running variable would violate the assumption of a sufficiently large number of mass points described by Cattaneo et al. (2024).

⁴³To ensure that this approach is valid, I replicated the results on labor market success using the same estimation equation. Figure XX in the appendix shows that the results on employment probability point into the same direction.

⁴⁴The likelihood of PTSD was 4% for former forced workers vs. 1.5% for other individuals. Note that the survey did not rely on exogenous variation in having been a forced worker.

was more prevalent in their respective location (both in the Netherlands and in Germany).

I split the sample based on differences in the employment share of high-paying industries in the home municipality and the German counties: Individuals from Dutch municipalities who on average went to German counties that had a higher share of high-paying industries than their home municipality had a higher likelihood to gain skills in high-paying industries than they would have had at home. On the other hand, individuals from Dutch municipalities who went to counties with less high-paying industries would have been more likely to acquire skills in industries which were less well-paying in the 1970s than if they had not been conscripted into forced labor. Figure 11d shows that the negative effects of forced labor on employment are driven completely by the latter group, so individuals who had a downgrade in their type of industry exposure.

One possible explanation for this finding could be that forced workers who were more likely to gain experience in high-paying industries in Germany have higher earning opportunities in the Netherlands, thus not negatively impacting their labor force participation. Workers who acquired work experience in lower-paying industries than in the absence of conscription on the other hand have a disadvantage in their possible earnings in 1971, thereby lowering their expected earnings if employed and thus lowering their labor force participation. To more formally test for this, I repeated the heterogeneity analysis with an indicator variable for whether an individual is employed in such a high-paying industry in 1971 (excluding unemployed individuals). Figure ?? shows that neither group of forced workers differ significantly in their probability to be employed in a high-paying industry, but the directions of the effect would be in line with the notion that exposure to higher high-paying industries does indeed increase the probability to later be employed in such an industry, while the opposite effect has a negative sign.

5 Conclusion

In this project, I study how being conscripted into forced labor affects later labor market success. I exploit exogenous variation in the probability to be experience forced labor by studying the setting of Dutch male civilians who were conscripted to work in Germany during WWII based on their date of birth. Using a Regression Discontinuity Design, I find that individuals who were conscripted into forced labor (were either deported to Germany or were forced to go into hiding) have lower labor market success in 1971, more than 25 years after the former forced workers returned to the Netherlands in 1945.

Specifically, I find that individuals who were born within the conscripted cohorts have lower education, lower income and a lower likelihood to be employed. These negative effects are mostly driven by individuals who were exposed to harsher living conditions while in Germany. For this group, the forced labor conscription is also associated with worse physical health. Suggestive evidence also points towards lower psychological well-being of conscripted individuals. Taken together, this implies that the forced labor conscription led to persistent lower labor market success due to adverse effects on an individuals' health and well-being. I also present evidence that being exposed to higher-paying industries in Germany than in an individuals' place of origin mitigates some of the negative effects, possibly due to forced workers being exposed and thus shifting their occupation to higher-paying sectors during their forced labor experience. I find no effect of being conscripted into forced labor on family formation.

When applying my findings to contexts beyond the forced labor regime of Nazi Germany, a key policy implication is the need to provide adequate support to former forced workers upon their return to heir home countries to avoid that the possibly traumatic experiences lead to long-term disadvantages in the labor market. In the Netherlands, the former forced workers faced suspicion of collaboration with the enemy, leading them to remain silent about their experiences. This may have prevented affected individuals from seeking help, thus exacerbating and perpetuating their losses on the labor market. Additionally, it may be

beneficial to understand which skills former forced workers might have acquired during their forced labor experience, as I have shown that the negative effects are less pronounced when people were able to gain some experience in sectors in which they had the chance to work in upon return. Encouraging the application of these skills in future work opportunities may help lessen the negative effects of forced labor in the medium and long-run.

References

- (1943). Ergebnisse der jahrgansweisen Erfassung der Niederländer. Jahrgänge 1924, 1923, 1922.
- Abramitzky, R., Boustan, L., Eriksson, K., Feigenbaum, J., and Pérez, S. (2021). Automated Linking of Historical Data. *Journal of Economic Literature*, 59(3):865–918.
- Althausen, M. (1999). Niederländische Zwangsarbeiter in Berlin. In Spanjer, R., Oudesluijs, D. M., and Meijer, J., editors, *Zur Arbeit gezwungen: Zwangsarbeit in Deutschland 1940-1945*, pages 173–180. Edition Temmen, Bremen.
- Angrist, J., Chen, S. H., and Frandsen, B. R. (2010). Did Vietnam veterans get sicker in the 1990s? The complicated effects of military service on self-reported health. *Journal of Public Economics*, 94(11-12):824–837. Publisher: Elsevier.
- Angrist, J. D. (1990). Lifetime Earnings and the Vietnam Era Draft Lottery: Evidence from Social Security Administrative Records. *American Economic Review*, 80(3):313–336. Publisher: American Economic Association.
- Bauer, T. K., Braun, S., and Kvasnicka, M. (2013). The Economic Integration of Forced Migrants: Evidence for Post-War Germany. *The Economic Journal*, 123(571):998–1024.
- Bauer, T. K., Giesecke, M., and Janisch, L. M. (2019). The Impact of Forced Migration on Mortality: Evidence From German Pension Insurance Records. *Demography*, 56(1):25–47.
- Becker, S. O. (2022). Forced displacement in history: Some recent research. *Australian Economic History Review*, 62(1):2–25.
- Becker, S. O., Grosfeld, I., Grosjean, P., Voigtländer, N., and Zhuravskaya, E. (2020). Forced Migration and Human Capital: Evidence from Post-WWII Population Transfers. *American Economic Review*, 110(5):1430–1463.
- Beening, A. (2003). Der Kampf um Anerkennung: Ehemalige Zwangsarbeiter aus den Niederlanden. *Jahrbuch / Zentrum für Niederlande-Studien*, 14:105–119.
- Bertocchi, G. and Dimico, A. (2014). Slavery, education, and inequality. *European Economic Review*, 70(C):197–209.
- Blattman, C. and Annan, J. (2010). The Consequences of Child Soldiering. *The Review of Economics and Statistics*, 92(4):882–898.
- Bramsen, I. (1998). Gedwongen tewerkstelling tijdens de Tweede Wereldoorlog: Verwerkingsproblemen onder ex-dwang-arbeiders en de zorgdruk voor partners. *ICODO Info*, 15(1):5–12.
- Braun, S. T. and Franke, R. (2021). A county-level database on expellees in West Germany, 1939–1961. ISSN: 0340-8728 Version Number: 1.
- Braun, S. T. and Stuhler, J. (2023). Exposure to War and its Labor Market Consequences Over the Life Cycle. *SSRN Electronic Journal*.
- Buggle, J. C. and Nafziger, S. (2021). The Slow Road from Serfdom: Labor Coercion and Long-Run Development in the Former Russian Empire. *The Review of Economics and Statistics*, 103(1):1–17.
- Buonanno, P. and Vargas, J. F. (2019). Inequality, crime, and the long run legacy of slavery. *Journal of Economic Behavior & Organization*, 159(C):539–552.
- Cattaneo, M. D., Idrobo, N., and Titiunik, R. (2019). A Practical Introduction to Regression Discontinuity Designs: Foundations. *Elements in Quantitative and Computational Methods for the Social Sciences*.

- Cattaneo, M. D., Idrobo, N., and Titiunik, R. (2024). A Practical Introduction to Regression Discontinuity Designs: Extensions. *Elements in Quantitative and Computational Methods for the Social Sciences*.
- CBS (1934). *Uitkomsten van de Beroepstelling 1930*. Algemene Landsdrukkerij, 's-Gravenhage.
- CBS (1947). *Economische en sociale Kroniek der oorlogsjaren 1940 - 1945*. De Haan, Utrecht.
- Cinnirella, F. and Hornung, E. (2016). Landownership concentration and the expansion of education. *Journal of Development Economics*, 121(C):135–152.
- Conti, G., Poupakis, S., Ekamper, P., Bijwaard, G. E., and Lumey, L. H. (2024). Severe pre-natal shocks and adolescent health: Evidence from the Dutch Hunger Winter. *Economics & Human Biology*, 53:101–372.
- de Zwarte, I. (2020). *The Hunger Winter: Fighting Famine in the Occupied Netherlands, 1944–1945*. Studies in the Social and Cultural History of Modern Warfare. Cambridge University Press, Cambridge.
- Dell, M. (2010). The persistent effects of peru’s mining mita. *Econometrica*, 78(6):1863–1903.
- Deryugina, T., Kawano, L., and Levitt, S. (2018). The Economic Impact of Hurricane Katrina on Its Victims: Evidence from Individual Tax Returns. *American Economic Journal: Applied Economics*, 10(2):202–233.
- Fujiwaray, T., Laudaresz, H., and Caicedo, F. V. (2017). Tordesillas, slavery and the origins of brazilian inequality.
- Gelman, A. and Imbens, G. (2019). Why High-Order Polynomials Should Not Be Used in Regression Discontinuity Designs. *Journal of Business & Economic Statistics*, 37(3):447–456. Publisher: Taylor & Francis _eprint: <https://doi.org/10.1080/07350015.2017.1366909>.
- Grüter, R. and Mourik, A. v. (2020). Dutch Repatriation from the Former Third Reich and the Soviet Union: Political and Organizational Encounters and the Role of the Netherlands Red Cross. *Historical Social Research*, 45(4):151–172.
- Herbert, U. (1999). *Fremdarbeiter: Politik und Praxis des Ausländer-Einsatzes in der Kriegswirtschaft des Dritten Reiches*. Dietz, Bonn, neuaufl. edition.
- Hjalmarsson, R. and Lindquist, M. J. (2019). The Causal Effect of Military Conscription on Crime*. *The Economic Journal*, 129(622):2522–2562.
- Homze, E. L. (1967). *Foreign Labor in Nazi Germany*. Princeton University Press.
- Huttunen, K., Møen, J., and Salvanes, K. G. (2011). How Destructive Is Creative Destruction? Effects of Job Loss on Job Mobility, Withdrawal and Income. *Journal of the European Economic Association*, 9(5):840–870.
- Höschler, C. and Panek, I., editors (2019). *Zweierlei Suche: Fundstücke zu Displaced Persons in Arolsen nach 1945*. Arolsen Archives, Bad Arolsen.
- Ichino, A., Schwerdt, G., Winter-Ebmer, R., and Zweimüller, J. (2017). Too old to work, too young to retire? *The Journal of the Economics of Ageing*, 9:14–29.
- ILO (2022). *Global estimates of modern slavery forced labour and forced marriage*. Geneva.
- Imbens, G. and Klaauw, W. V. D. (1995). Evaluating the Cost of Conscription in The Netherlands. *Journal of Business & Economic Statistics*, 13(2):207–215. Publisher: Taylor & Francis _eprint: <https://www.tandfonline.com/doi/pdf/10.1080/07350015.1995.10524595>.
- Jongbloed, A. (1996). *Voor koning(in) en vaderland: Dienstplicht door de jaren heen*. ALPHA, Zutphen.
- Kesternich, I., Siflinger, B., Smith, J. P., and Winter, J. K. (2014). The Effects of World

- War II on Economic and Health Outcomes across Europe. *The Review of Economics and Statistics*, 96(1):103–118.
- Kommission Der Europäischen Gemeinschaften (2012). Eurobarometer 3–42. Version Number: 1.1.0 Type: dataset.
- Kuck, C. (2010). NiederlandeNet – Geschichte - Niederländische Zwangsarbeiter - Wirtschaft und Arbeitslosigkeit in den Niederlanden vor Beginn der Besatzungszeit.
- Lagrou, P. (1999). *The Legacy of Nazi Occupation: Patriotic Memory and National Recovery in Western Europe, 1945–1965*. Studies in the Social and Cultural History of Modern Warfare. Cambridge University Press, Cambridge.
- Lak, M. (2016). Trading with the Enemy? In *Paying for Hitler’s War: The Consequences of Nazi Hegemony for Europe*, pages 140–163. Cambridge University Press.
- LeBaron, G., editor (2018). *Researching forced labour in the global economy: methodological challenges and advances*. Number 220 in Proceedings of the British Academy. The British Academy by Oxford University Press, Oxford, first edition edition.
- Lofti, G. (2000). Niederländische Zwangsarbeiter in Arbeitserziehungslagern der Gestapo. In Fasse, N., Houwink ten Cate, J. T. M., and Lademacher, H., editors, *Nationalsozialistische Herrschaft und Besatzungszeit: historische Erfahrung und Verarbeitung aus niederländischer und deutscher Sicht*, number Bd. 1 in Studien zur Geschichte und Kultur Nordwesteuropas, pages 257–264. Waxmann, Münster ; New York. OCLC: ocm47898877.
- Markevich, A. and Zhuravskaya, E. (2018). The economic effects of the abolition of serfdom: Evidence from the russian empire. *American Economic Review*, 108(4-5):1074–1117.
- Marx, H. (2019). *Die Verwaltung des Ausnahmezustands: Wissensgenerierung und Arbeitskräfte lenkung im Nationalsozialismus*. Geschichte des Reichsarbeitsministeriums im Nationalsozialismus. Wallstein Verlag, Göttingen.
- Meertens Instituut (nd.). Nederlandse Voornamenbank.
- Mitchener, K. J. and McLean, I. W. (2003). The productivity of us states since 1880. *Journal of Economic Growth*, 8(1):73–114.
- NIOD Inst. v. Oorlogs-, Holocaust- en Genocidestudies, Nederlands Instituut voor Militaire Historie (NIMH), and Kon. Inst. v. Taal-, Land- en Volkenkunde (KITLV) (2022). *Over de grens: Nederlands extreem geweld in de Indonesische onafhankelijkheidsoorlog, 1945-1949*. Amsterdam University Press, Amsterdam.
- Nunn, N. (2008). *Slavery, Inequality, and Economic Development in the Americas: An Examination of the Engerman-Sokoloff Hypothesis*, pages 148–180. Harvard University Press, Cambridge.
- Oreopoulos, P., von Wachter, T., and Heisz, A. (2012). The Short- and Long-Term Career Effects of Graduating in a Recession. *American Economic Journal: Applied Economics*, 4(1):1–29.
- Peters, M. (2022). Market Size and Spatial Growth—Evidence From Germany’s Post-War Population Expulsions. *Econometrica*, 90(5):2357–2396.
- Pfahlmann, H. (1968). *Fremdarbeiter und Kriegsgefangene in der deutschen Kriegswirtschaft 1939-1945*. Beiträge zur Wehrforschung. Wehr und Wissen Verlagsgesellschaft, Darmstadt.
- Proudfoot, M. J. (1957). *European Refugees: 1939-52 : A study in forced population movement*. Faber and Faber, London.
- Ramirez, D. and Haas, S. A. (2022). Windows of Vulnerability: Consequences of Exposure Timing during the Dutch Hunger Winter. *Population and Development Review*, 48(4):959–

- Richardson, A. (2000). Children, Youth and Schooling Disruption in the Netherlands During World War II. *Groniek*, (148). Number: 148.
- Sarvimäki, M., Uusitalo, R., and Jäntti, M. (2022). Habit Formation and the Misallocation of Labor: Evidence from Forced Migrations. *Journal of the European Economic Association*, 20(6):2497–2539.
- Schwandt, H. and von Wachter, T. (2020). Socio-Economic Decline and Death: The Life-Cycle Impacts of Recessions for Labor Market Entrants. Technical Report w26638, National Bureau of Economic Research, Cambridge, MA.
- Schwank, H. (2024). Disruptive Effects of Natural Disasters: The 1906 San Francisco Fire. CRC TR 224 Discussion Paper Series crctr224_2024_71, *University of Bonn and University of Mannheim, Germany*.
- Sijes, B. A. (1966). *De arbeidsinzet: De gedwongen arbeid van Nederlanders in Duitsland, 1940-1945*. Martinus Nijhoff, Den Haag.
- Soares, R., Assunção, J. J., and Goulart, T. F. (2012). A note on slavery and the roots of inequality. *Journal of Comparative Economics*, 40(4):565–580.
- Spoerer, M. (2001). *Zwangsarbeit unter dem Hakenkreuz: ausländische Zivilarbeiter, Kriegsgefangene und Häftlinge im Deutschen Reich und im besetzten Europa 1939-1945*. Deutsche Verlags-Anstalt, Stuttgart.
- Spoerer, M. and Fleischhacker, J. (2002). Forced Laborers in Nazi Germany: Categories, Numbers, and Survivors. *The Journal of Interdisciplinary History*, 33(2):169–204.
- Stiftung Erinnerung, Verantwortung und Zukunft (2017). *The German compensation program for forced labor: practice and experiences*. Stiftung Erinnerung, Verantwortung und Zukunft, Berlin.
- Tooze, J. A. (2006). *The wages of destruction: the making and breaking of the Nazi economy*. Allen Lane, London ; New York.
- Van Eden, C. (1946). The Education of the Youth. *The ANNALS of the American Academy of Political and Social Science*, 245(1):129–143.
- von Wachter, T. (2020). The Persistent Effects of Initial Labor Market Conditions for Young Adults and Their Sources. *Journal of Economic Perspectives*, 34(4):168–194.
- Warmbrunn, W. (1972). *The Dutch under German occupation: 1940-1945*. Stanford Univ. Pr, Stanford, Calif, repr edition.

Figures

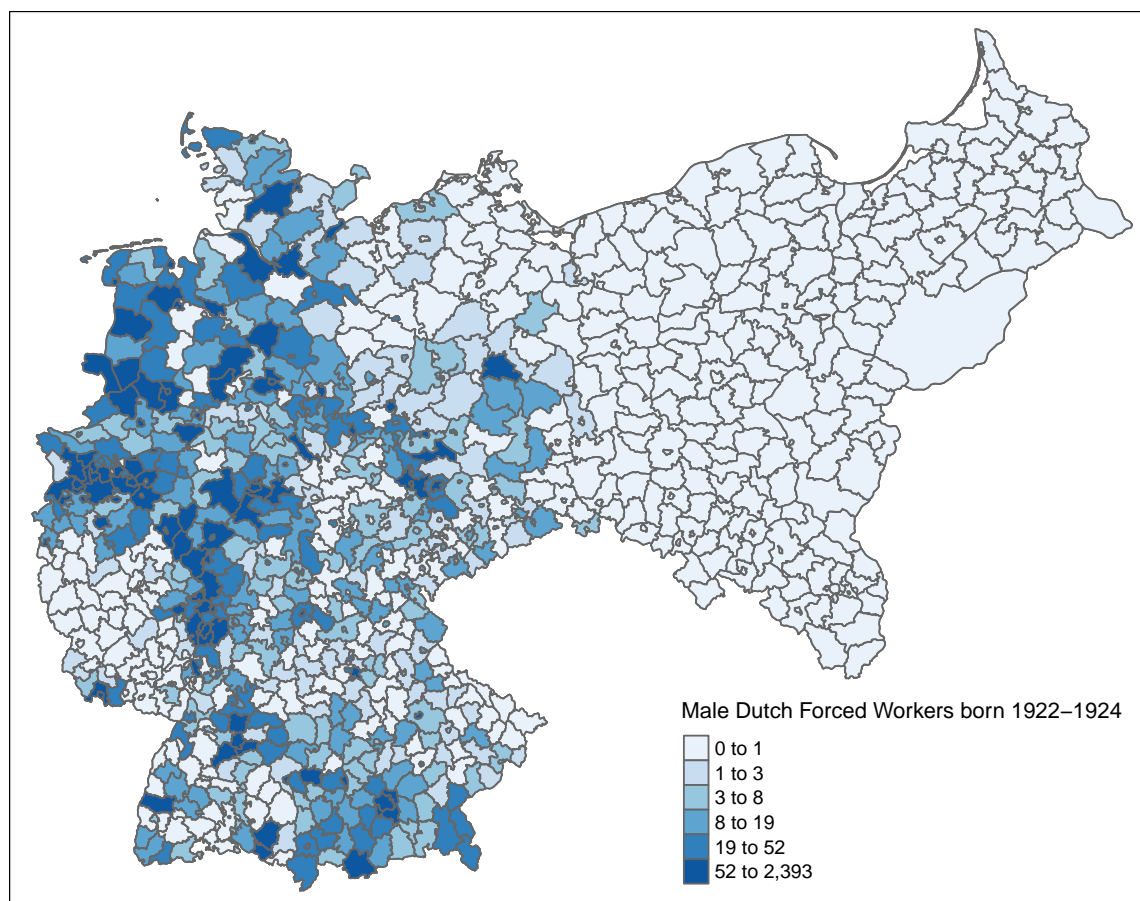


Figure 1: Regional Distribution of Male Dutch Forced Workers born 1922-1924 across German counties

Notes. This figure shows the number of male Dutch forced workers born between 1922 and 1924 based on data by the Arolsen Archives, excluding double-entries of identical individuals. Gender was assigned using first names and data from Meertens Instituut (nd).

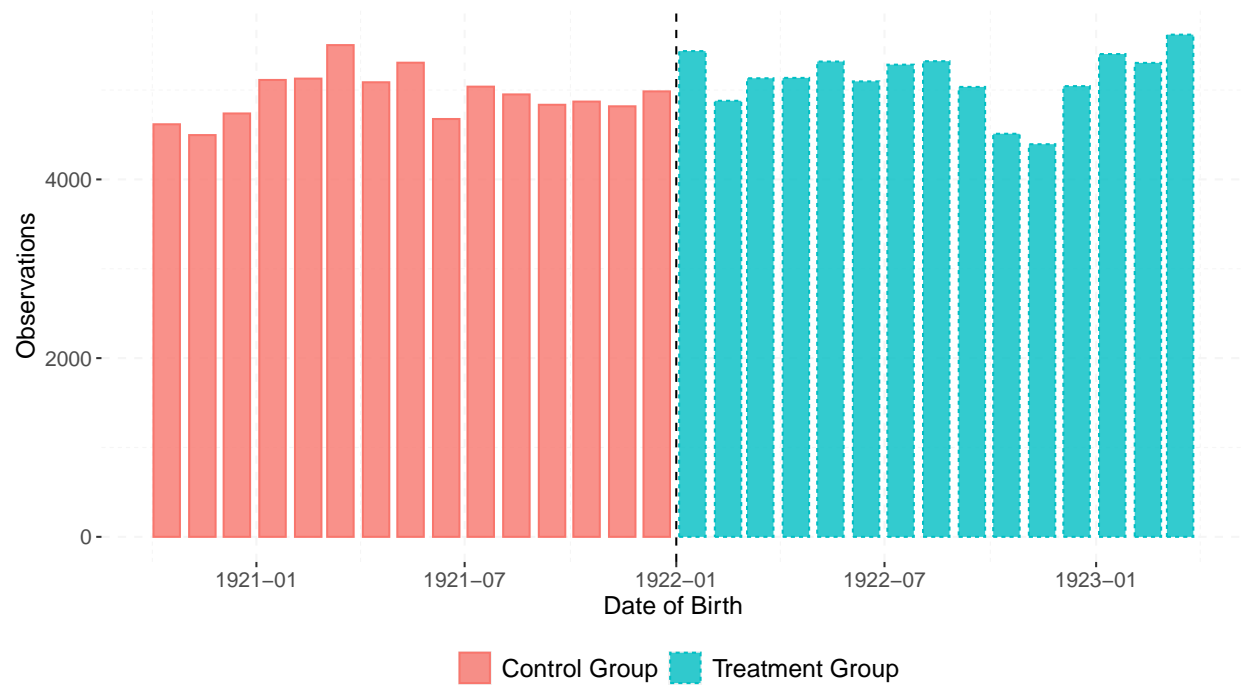


Figure 2: Number of male observations per month and year of birth based on the 1971 Census

Notes. This figure shows the number of male individuals for each month and year of birth in the 1971 Census in a 15 month bandwidth around the cutoff of treatment, January 1, 1922.

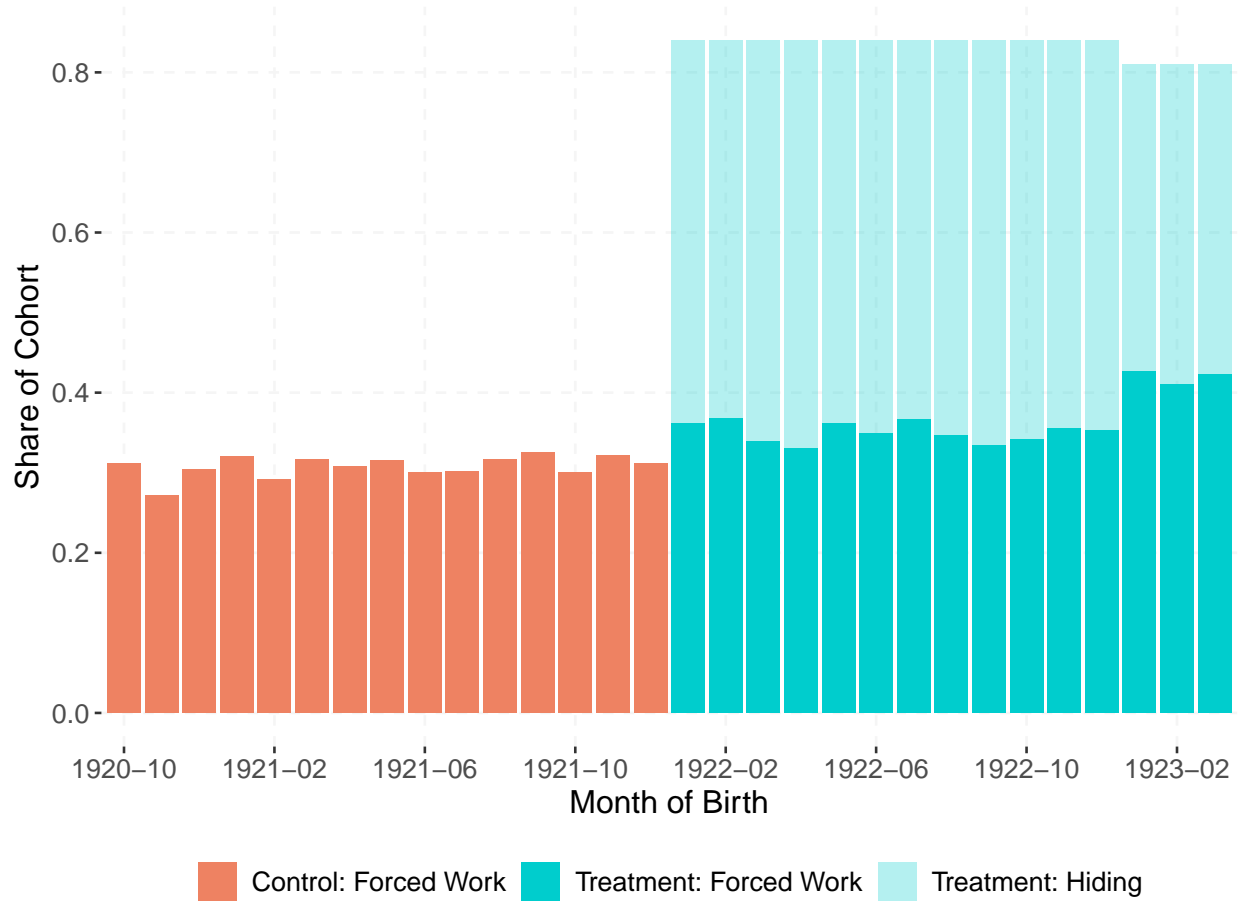


Figure 3: Number of treated individuals

Notes. This figure shows the number of male treated individuals for each month and year of birth in the 1971 Census in a 15 month bandwidth around the cutoff of treatment, January 1, 1922. The numbers of forced workers is derived by comparing the sample size in the Arolsen archival records to the sample size in the census data 1971. The share of men who went into hiding is derived by subtracting the number on the share of men who were granted an exception taken from German records from 1943, which is available separately for each cohort.

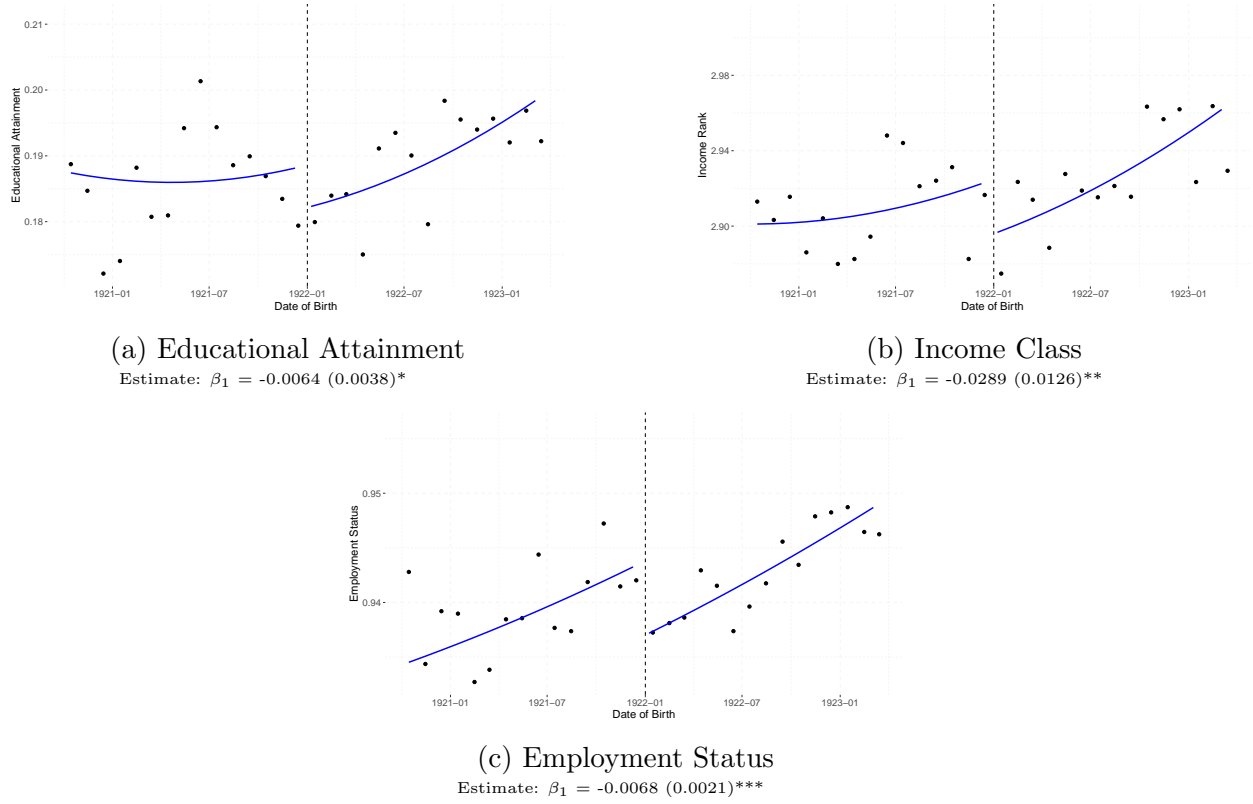


Figure 4: RDD Effects of Forced Labor Conscription on Labor Market Outcomes based on 1971 Census

Notes. The figures show the average of labor market outcomes based on the 1971 Census for each month and year of birth, and the regression line based on an RDD estimation using a 15 months bandwidth, a triangular kernel, and polynomial of the running variable of degree two using the underlying individual-level data. Panel a shows effect on the probability of finishing secondary education, panel b shows the income class measured from 0 to 5 in steps of 4,000 Dutch Guilder, and panel c shows the employment status taking a value of zero or one. The y-axis is normalized to 10% of a standard deviation for each respective outcome.

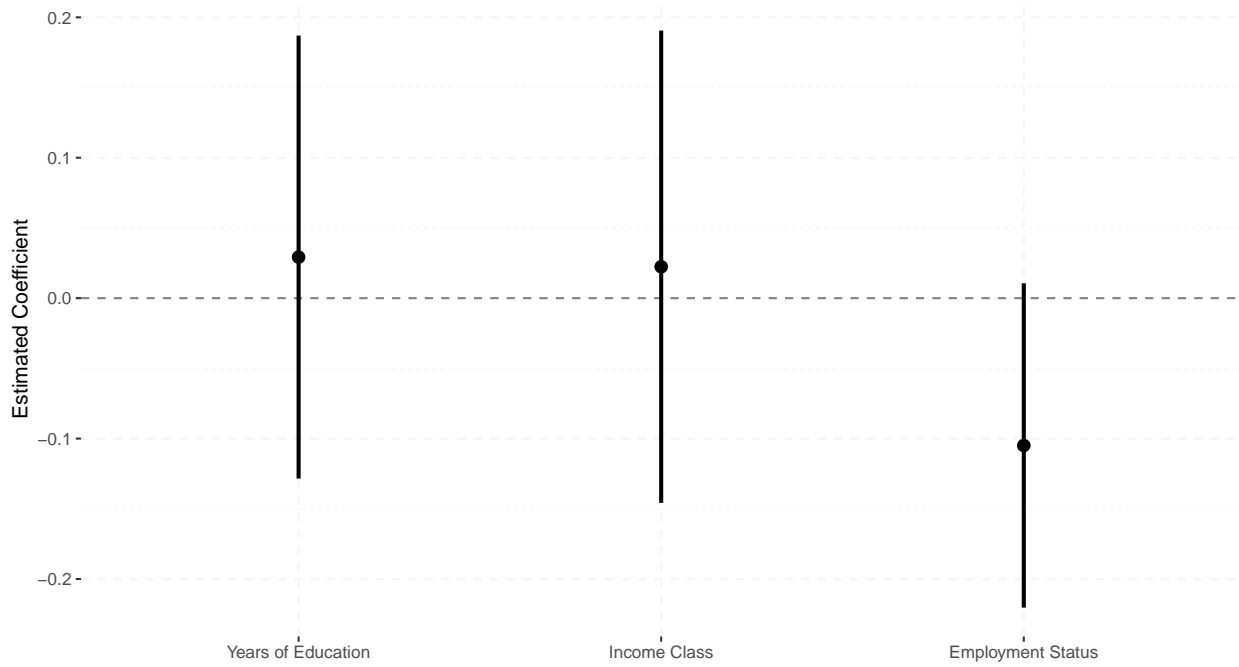


Figure 5: Effects of Forced Labor Conscription on Labor Market Outcomes using 1975-1944 Eurobarometer

Notes. This figure shows the estimated coefficients of a simple differences estimation using Eurobarometer data from 1975 to 1994. Years of education is measured from 7 to 15, income class is measured from 1 to 12, and employment status takes a value of zero. The 95% confidence intervals and the estimates are standardized by the standard deviation of the respective dependent variable.

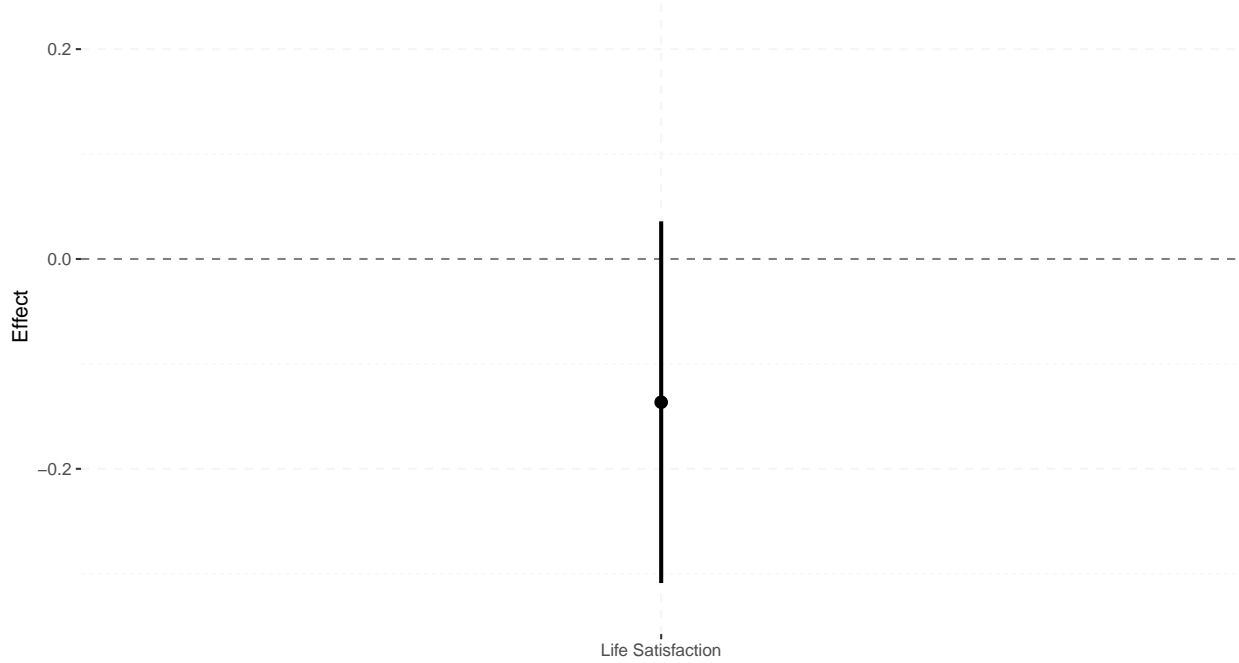


Figure 6: Effects of Forced Labor Conscription on Life Satisfaction using 1975-1944 Eurobarometer

Notes. This figure shows the estimated coefficient of a simple differences estimation using Eurobarometer data from 1975 to 1994. Life satisfaction is measured from 0 to 3. The 95% confidence intervals and the estimate are standardized by the standard deviation of the respective dependent variable.

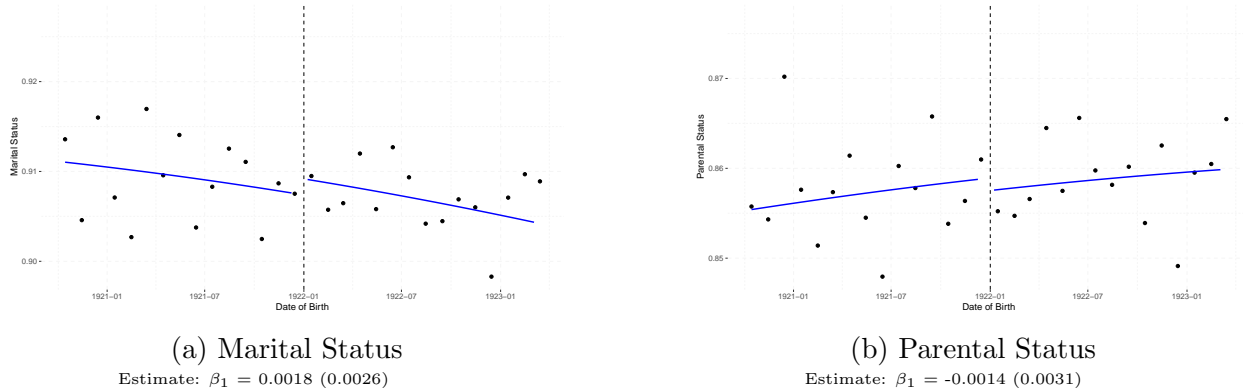


Figure 7: RDD Effects of Forced Labor Conscription on Family Formation based on 1971 Census

Notes. The figures show the average family formation outcomes based on the 1971 Census for each month and year of birth, and the regression line based on an RDD estimation using a 15 months bandwidth, a triangular kernel, and polynomial of the running variable of degree two using the underlying individual-level data. Panel a shows a dummy which takes the value of one if married, and zero otherwise. Panel b shows a dummy which takes the value of one if an individual has a child, and zero otherwise. The y-axis is normalized to 10% of a standard deviation for each respective outcome.

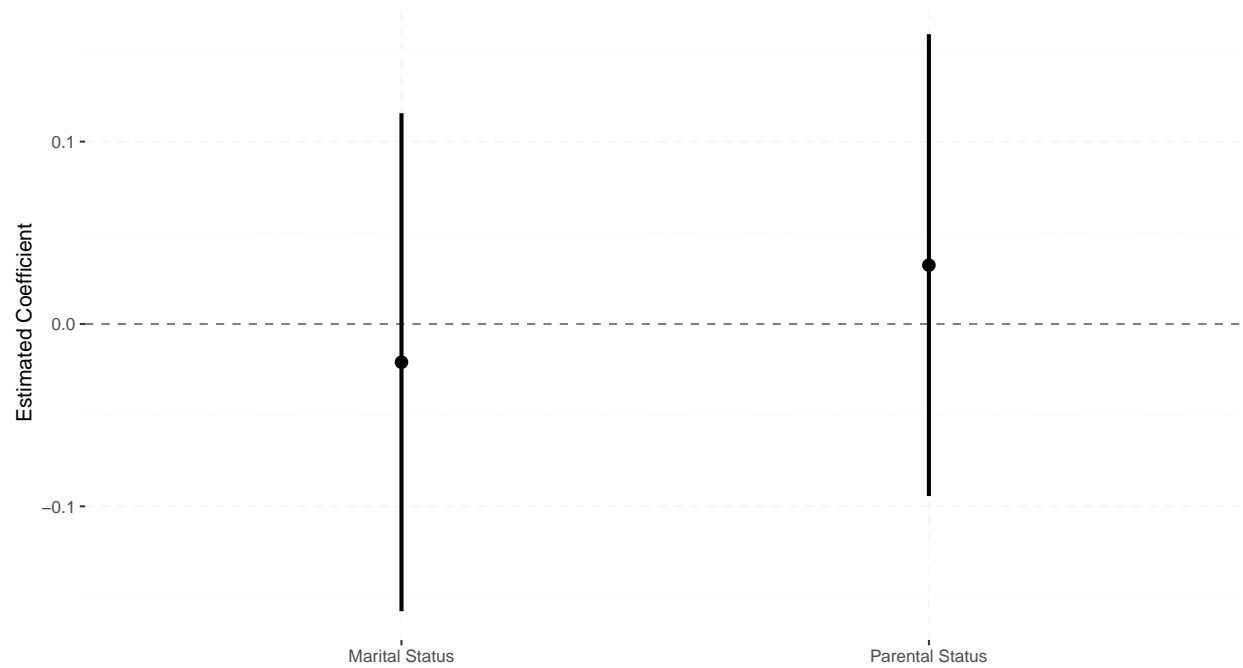
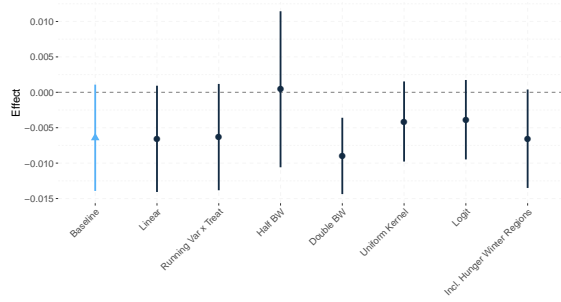
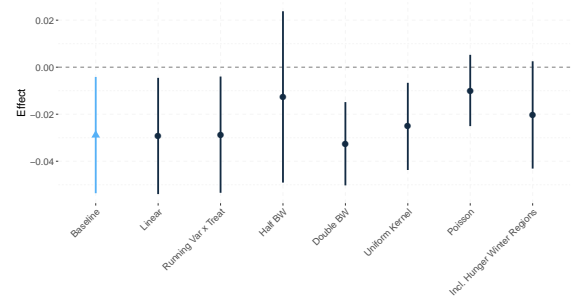


Figure 8: Effects of Forced Labor Conscription on Family Formation using 1975-1944 Eurobarometer

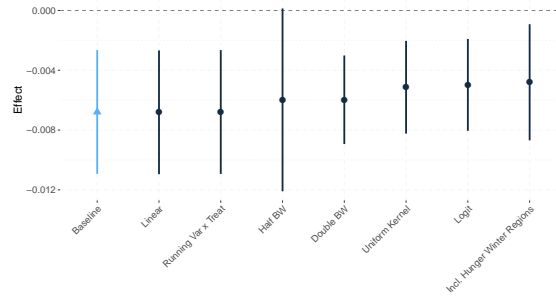
Notes. This figure shows the estimated coefficients of a simple differences estimation using Eurobarometer data from 1975 to 1994. Marital status is a dummy which takes the value of one if married, and zero otherwise, and parental status is a dummy which takes the value of one if an individual has a child, and zero otherwise. The 95% confidence intervals and the estimates are standardized by the standard deviation of the respective dependent variable.



(a) Educational Attainment



(b) Income Class



(c) Employment Status

Figure 9: Robustness of RDD Effects of Forced Labor Conscription on Labor Market Outcomes based on 1971 Census

Notes. This figure shows RDD regressions using the 1971 Census with different specifications. The bars show the 95% confidence interval.

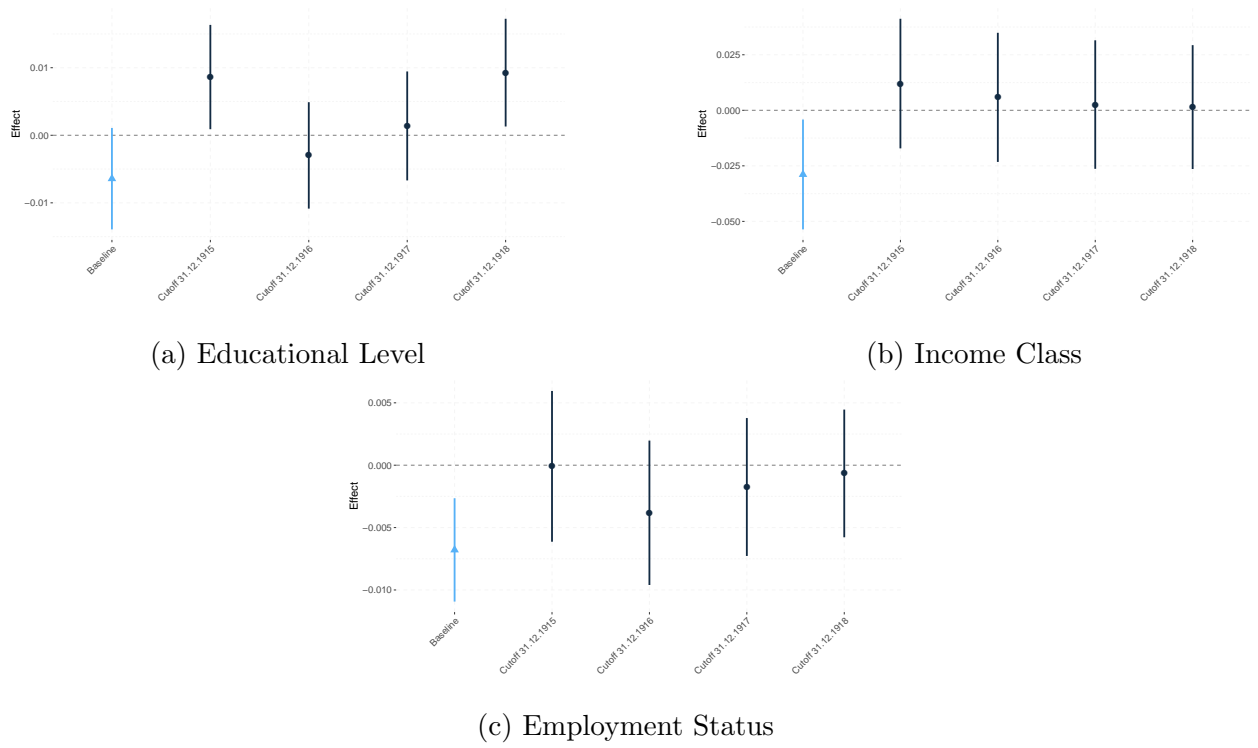
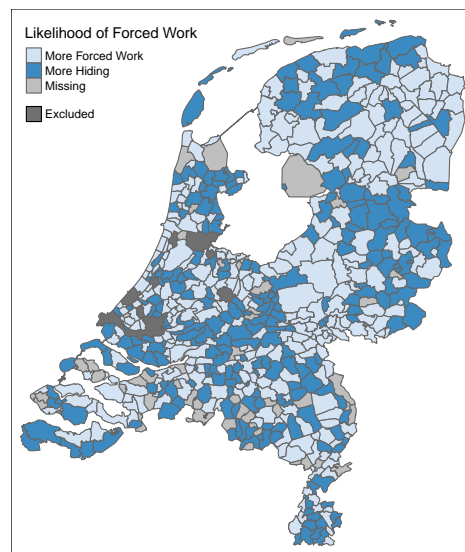
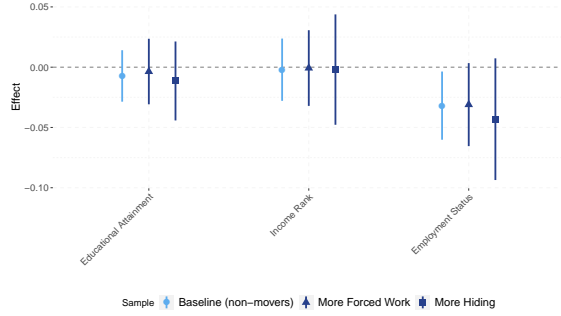


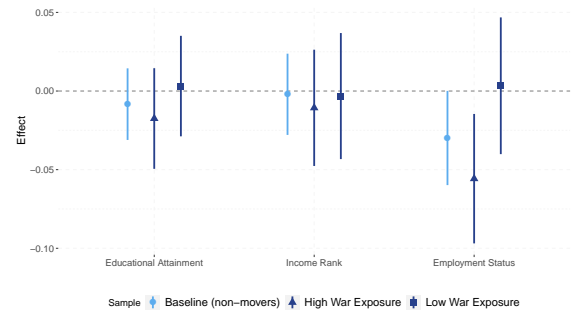
Figure 10: Placebo RDD Effects of Forced Labor Conscription on Labor Market Outcomes based on 1971 Census

Notes. This figure shows RDD regressions using a 15 months bandwidth, a triangular kernel, and polynomial of the running variable of degree two using the 1971 Census with different placebo cutoffs. The bars show the 95% confidence interval.

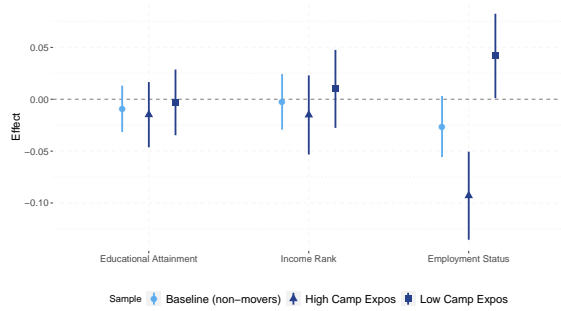




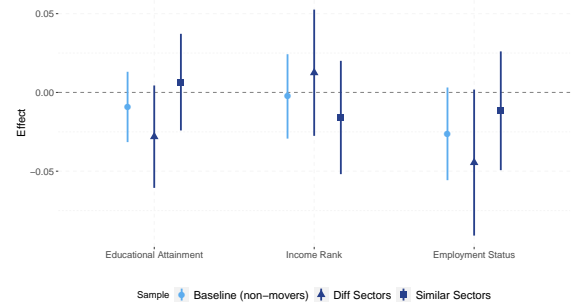
(a) Heterogeneity by share of forced workers



(b) Heterogeneity by War Exposure in DE



(c) Heterogeneity by Camp Exposure in DE



(d) Heterogeneity by Difference in Industry Structure

Figure 11: Heterogeneous RDD Effects of Forced Labor Conscription on Labor Market Outcomes based on 1971 Census

Notes. This figure shows RDD regressions using a 15 months bandwidth, a triangular kernel, and polynomial of the running variable of degree two for economic outcomes using the 1971 Census with subsamples. In panel a, the sample is split by the median share of conscripted individuals from a Dutch municipality who can be found in the data provided by the Arolsen Archives. In panel b, the sample is split by the median of the average weighted exposure of forced workers from a Dutch municipality to houses damaged in West Germany. In panel b, the sample is split by the median of the average weighted exposure of forced workers from a Dutch municipality to labor education camps in Germany. In panel c, the sample is split by the median of the difference in the employment share in Dutch municipalities and the average weighted employment share in German counties that forced workers from each Dutch municipality were exposed to. The bars show the 95% confidence interval. The coefficients and confidence intervals are by the standard deviation of the respective dependent variable.

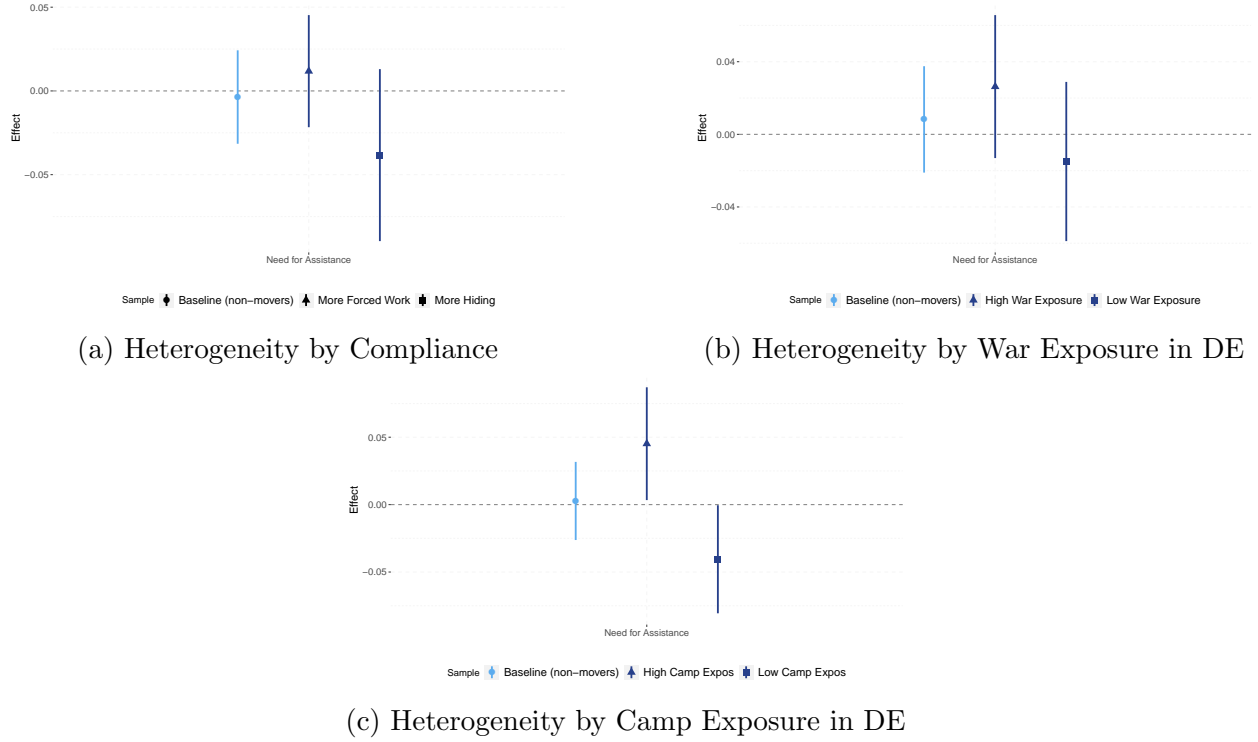


Figure 12: Heterogeneous RDD Effects of Forced Labor Conscription on Need for Assistance based on 1971 Census

Notes. This figure shows RDD regressions using a 15 months bandwidth, a triangular kernel, and polynomial of the running variable of degree two for the need of assistance in daily life using the 1971 Census with subsamples. In panel a, the sample is split by the median share of conscripted individuals from a Dutch municipality who can be found in the data provided by the Arolsen Archives. In panel b, the sample is split by the median of the average weighted exposure of forced workers from a Dutch municipality to houses damaged in West Germany. In panel c, the sample is split by the median of the average weighted exposure of forced workers from a Dutch municipality to labor education camps in Germany. The bars show the 95% confidence interval.

Tables

Variable	Levels	Mean Overall	Std. Dev. Overall
Educational Attainment	Finished Secondary Education: Yes/No	0.188	0.39
Income Rank	0-5 (4,000 Dutch guilder range)	2.918	1.362
Employment Status	Employed: Yes/No	0.941	0.235
Skill Level of Occupation	Above Low Skilled Occupation: Yes/No	0.468	0.499
Marital Status	Married: Yes/No	0.908	0.289
Parental Status	Has a Child: Yes/No	0.858	0.349
Need for Assistance	Yes/No	0.038	0.191
Observations		151080	151080

Table 1: Descriptive Statistics

Table 2: Labor Market Effects

	<i>Dependent variable:</i>			
	Educational Attainment	Income Rank	Employment Status	Skill Level of Occupation
	(1)	(2)	(3)	(4)
RDD Estimate	−0.006* (0.004)	−0.029** (0.013)	−0.007*** (0.002)	−0.006 (0.005)
Observations	124490	141109	151080	151080
Bandwidth	15 months	15 months	15 months	15 months
Mean Dependent Variable	0.188	2.918	0.941	0.468

Note:

*p<0.1; **p<0.05; ***p<0.01

Table 3: Social Effects

	<i>Dependent variable:</i>	
	Marital Status	Parental Status
	(1)	(2)
RDD Estimate	0.002 (0.003)	−0.001 (0.003)
Observations	151080	151080
Bandwidth	15 months	15 months
Dependent Variable Range	0-1	0-1
Mean Dependent Variable	0.908	0.858

Note:

*p<0.1; **p<0.05; ***p<0.01

Variable	Levels	Mean Overall	Std. Dev. Overall	Mean Treatment	Mean Control
Years of Education	7-15	10.01	3.14	10.01	10.01
Income Class	1-12	7.13	3.23	7.23	7.04
Employment Status	0-1	0.38	0.49	0.37	0.40
Occupational Rank	1-7	4.17	1.94	4.02	4.31
Marital Status	0-1	0.84	0.37	0.84	0.84
Parental Status	0-1	0.10	0.31	0.12	0.09
Life Satisfaction	0-3	2.23	0.68	2.19	2.27

Table 4: Descriptive Statistics

Table 5: Labor Market Effects – Eurobarometer

	<i>Dependent variable:</i>			
	Years of Education	Income	Employment Probability	Occupation Type
	(1)	(2)	(3)	(4)
treatmentGroup	0.092 (0.252)	0.072 (0.277)	-0.051* (0.029)	-0.327 (0.254)
Wave FE	YES	YES	YES	YES
Dependent Variable Range	14-22	1-12	0-1	
Mean Dependent Variable	16.46	6.32	0.21	
Observations	615	505	620	237
R ²	0.084	0.187	0.482	0.146
Adjusted R ²	0.006	0.108	0.438	-0.023

Note: *p<0.1; **p<0.05; ***p<0.01
Standard Errors are clustered at wave level.

Table 6: Labor Market Effects – Eurobarometer

	<i>Dependent variable:</i>		
	Marital Status	Children	Life Satisfaction
	(1)	(2)	(3)
treatmentGroup	-0.008 (0.031)	0.010 (0.024)	-0.093 (0.060)
Wave FE	YES	YES	YES
Dependent Variable Range	0-1	0-1	
Mean Dependent Variable	0.73	0.08	
Observations	612	620	492
R ²	0.092	0.218	0.137
Adjusted R ²	0.014	0.152	0.063

Note: *p<0.1; **p<0.05; ***p<0.01
Standard Errors are clustered at wave level.

Appendix A.

5.1 Data

5.1.1 Removing duplicate entries in Arolsen Archive data

The Arolsen Archive on forced workers in Germany includes information on the full name, date of birth, location of birth, and the location where the person stayed in Germany. The original sample consists of 594,967 observations. Some individuals show up more than once in the data because multiple sources have been aggregated for the archival records.

I therefore use a fuzzy linkage method to link duplicate entries of the same person to one another to be able to exclude double-counts of individuals. I follow the Abramitzky, Boustan, and Eriksson (ABE) Algorithm (Abramitzky et al., 2021), and adjust their method according to my data availability. The ABE method uses variables which are unlikely to change over time, namely a person’s place of birth, name and age. To reduce computational requirements, only individuals with the same first letters of the first and last name, the same place of birth and an age difference of up to 5 years are compared (so-called blocking). Of the total XX observations of the archival data on forced workers, only XX have information on their place of birth. Because of this, I cannot reasonably block on the place of birth without not linking a majority of the observations. In contrast, I do know the exact date of birth for XX (XX percent) of the observations instead of only their self-reported age as in the census data for which the ABE-JW method was derived. This alleviates the issues connected to only knowing individuals’ age, such as rounding of reported age and differences in age at different points in time of reporting. I therefore block on the date of birth and on the first letters of the first and last name instead⁴⁵. Following ABE-JW, for each of the possible matches within a block, I then calculate the string distance of the first name, last name and place of birth where available using the Jaro-Winkler string distance and restrict links to individuals for whom all available JW distances are less than or equal to 0.1⁴⁶⁴⁷. The ABE-JW method links two datasets where every individual only shows up once in each dataset, so a possible match is only linked if it is unique, and there are not multiple entries which are close to the original. In my case however, I am linking observations to other entries from the same dataset, and links to multiple entries are plausible because a person may show up more than twice in the archival records. I therefore do not restrict links to only those entries which have only one plausible match. I then treat all linked individuals as only one observation going

⁴⁵This means that ADD NUMBER observations, for whom either the date of birth, the first name or the last name is missing, remain unlinked and are treated as unique individuals.

⁴⁶The place of birth is reported for 30.5% of all entries.

⁴⁷Following ABE-JW, I use a weight of 0.1, which puts more weight on the first character of a string.

forward. Of the originally 594,967 observations, my algorithm links 121,561 observations to another entry, leaving 473,406 observations of probably unique individuals.

Since the archival data does not include the gender of the individuals, I use the data on first names and combine this with information on name frequency based on gender from the Corpus of First Names in the Netherlands published by Meertens Instituut (nd). Of the 34,831 unique first names in my dataset, 11,802 (33.9%) are part of the Corpus of First Names. To include names with slightly different spellings, I calculate the JW-distance between first names and assign the same gender to a name with a sufficiently similar name that is part of the Corpus of First Names (a JW-string distance of up to 0.1, as suggested by Abramitzky et al. (2021)). This yields an addition of 17,417 names. In total, I can assign a gender probability to 29,219 or 83.9% of all unique first names. Based on this, I calculate the probability of a given name to be male or female and classify names for which at least 70% of individuals with that name are either male or female respectively. All other names are classified as uncertain. 78.9% of all unique first names can be classified as either male or female using the cutoff of 70%. Since some persons have multiple first names (either because they have a middle name, or because two observations with differently spelled names were linked to the same individual), I use the mode of each persons' first names' genders to assign their gender⁴⁸ In total, I can assign a gender to 93.7% of individuals in the archival records. For the relevant cohorts of 1922 and 1924, there are 10.7% female and 84.2% male individuals.

ADD description of linking birth places of Arolsen Archives to 1971 Census.

5.1.2 Employment Structure

ADD detailed description of employment structure and industry classification of German counties and of Dutch municipalities.

5.2 Descriptives

5.3 Eurobarometer

ADD detailed description of how I harmonized the Eurobarometer data.

⁴⁸So if a person has two names, where one is classified as male and one is classified as uncertain, I assign this person a male gender. If a person has two male names and one female name, I assign a male gender as well. If a person has the same number of names being classified as male and female, I do not assign them a gender.

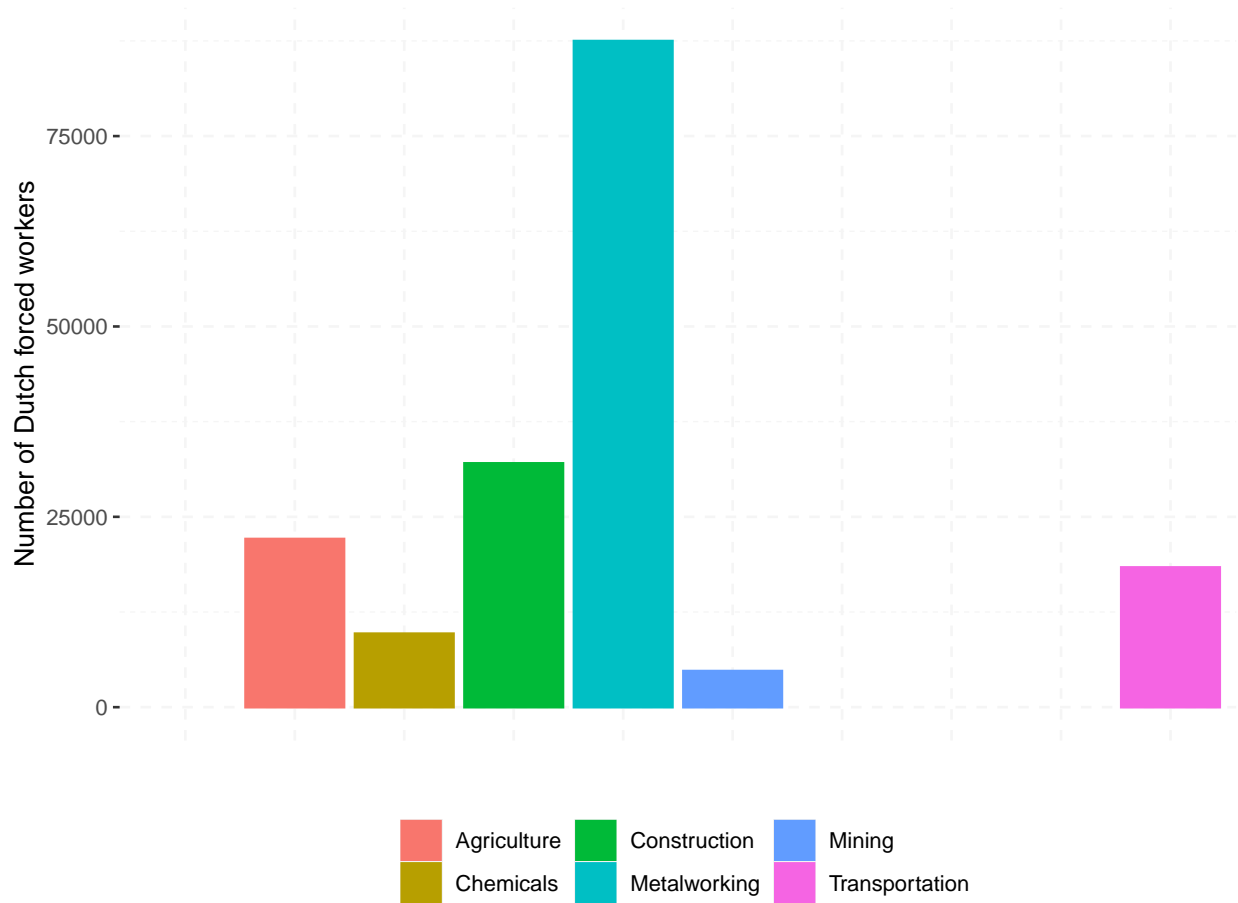


Figure 13: Allocation of Dutch forced workers across industries in Germany

Notes. The data is based on Herbert (1999) and shows the number of Dutch forced workers by industry in Germany.

I define the following treatment and control group, consisting of one age group respectively: The older control group consists of men born in 1920 or 1921, the older treatment group are men born in 1922 or 1923.

I estimate the following equation:

$$Y_{it} = \beta_0 + \beta_1 Treat_{it} + \lambda_t + \epsilon_{it} \quad (2)$$

where λ_t are wave fixed effects to control for differences in survey design between different waves. The outcomes of interest Y_{it} are years of education, income class, employment status and occupational rank (measuring the type of position a person has if employed). Figure 5 shows the results⁴⁹. While I find no significant differences in years of education or income, I

⁴⁹Table 5 shows the full regression results

again find that individuals of the treatment group are 5.1% less likely to participate in the labor market which is 10.4% of one standard deviation. The occupational rank is lower but insignificant..