Impact of Famine Exposure in Utero on Labor Market Behavior and Health Later in Life*

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Abstract

In this paper, we study the long-term causal effects of the Dutch Famine on labor market and health behavior later in life (55-70). To acknowledge the dynamic nature of labor market changes we focus on the impact of the famine on the timing of becoming disabled or retired. To acknowledge the dynamic nature of health behavior, medication use and health expenditures, we focus on the impact of the famine on the changes over time of medication use and health expenditures, both categorized. In all analyses we use a non-linear Difference-in-difference approach to identify the the causal impact of famine exposure in utero on later life outcomes.

We account for selective fertility, by restricting our analysis to those conceived before the famine, and for selective survival using either an inverse propensity weighting method or a Copula approach.

For the empirical analysis we used data of military recruits born around the Dutch famine (1944-1947) linked to the Dutch mortality register (deaths trough 2014) and linked to individual administrative data on the monthly labor market status (1999-2013), on the annual income (2003-2013), on annual prescribed medications (2006-2013), and, on annual insured health costs (2009-2013).

We find that famine exposure in the first trimester of gestation accelerates the timing of disability, decreases labor income and increases the expenditures for mental health. Exposure in the second trimester decreases expenditure for medications. Exposure in the third trimester increases medication use for mental diseases.

JEL classification: I10, J13, I14, I24.
Keywords:

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1 Introduction

An abundant economic literature has provided evidence that early life circumstances, even as early as in utero, affects outcomes later in life, including employment and earnings (Currie, 2009, Almond and Currie, 2011). The literature offers several theories for a relationship between early life events and outcomes later in life. The *fetal-origins hypothesis* (Barker, 1995, Almond and Currie, 2011, Almond et al., 2017) suggests a direct link from in utero circumstances to adult health that may be independent of social class in adult life. *Life course models* assume that health (socioeconomic) risks may accumulate over the life course (Ben Shlomo and Kuh, 2002). Studies for the UK (Case et al., 2005) and for the US (Case and Paxson, 2008) show that good health during early childhood lead to a higher economic status later in life.

In recent years, there has been increasing awareness of the potential of using famine exposure to measure the long-run effects of in utero malnutrition. The Dutch Famine (Hunger Winter) of 1944-45 with civilian starvation caused by war conditions (Lumey et al., 2011), provides a unique opportunity to analyze the the effect of maternal decreased nutritional intake during pregnancy on later life outcomes of children. The famine struck unexpectedly in a society without prior food shortages, the affected population had major problems obtaining food elsewhere. The famine was well defined in time (7 months) and space (cities in the West). Population was ethnically homogeneous without prior differences in dietary patterns. The details of this famine has been well documented (Stein et al., 1975, Burger et al., 1948, Lumey and van Poppel, 1994). After the German surrender in May 1945 the famine was soon over.

A few papers have investigated the impact of exposure to famine in utero on labor market outcomes later in life. Chen and Zhou (2007) estimated the impact of the great 1959-1961 famine in China on labor supply of the survivors They found that exposure to the famine reduced individual's working hours and income earned. Neelsen and Stratmann (2011) examined the long-run impact of the Greek 1941-1942 famine on human capital development. They found that exposure to this famine at young ages has impaired the educational attainment. Scholte et al. (2015) found that exposure to the Dutch famine in the first trimester of gestation reduces the individual employment rate later in life.

In contrast to Scholte et al. (2015) we do not look at the impact of the famine on the employment probability, but at the impact of the famine on the hazard rate of becoming disabled or retired. Just as Scholte et al. (2015) we do not observe the labor market history up till the first observation of the labor market status in January 1999, when the affected individuals are around 55 years of age. The chance to work at this age is very much related to the individual labor market experience. The timing of disability and retirement is less influenced by labor market experience. Receiving disability benefits shows that somebody is not able to work due to health problems and early retirement is often also related to health problems. By only looking at the probability of occupying a particular state at a particular time neglects, as Scholte et al. (2015) do, the dynamic nature of labor market behavior. By using the hazard rate of a labor market transition to investigate the impact of famine exposure we acknowledge this dynamic nature. A hazard rate model also takes (right)censoring, the fact that some events may not have occurred before the end of the observation window, into account. The parametric hazard model we formulate also allows us to account for disability or (early) retirement before the first observation time, so called left-truncation.

Another issue ignored by Scholte et al. (2015) is selective fertility due to the famine. The fertility in the Netherlands dropped dramatically in the months after the famine (and spiked a year later). It is very likely that women with less access to food were less likely to become pregnant, which implies that the men who were born have a more healthy/wealthy background. We do not observe the exact food intake, but by restricting our sample to those conceived before the famine struck, just as Conti et al. (2019) in our final analysis we effectively rule out selective fertility.

A final issue ignored by Scholte et al. (2015) is the possibility of selective survival, i.e. those still alive at the first moment the observation of the administrative data starts are not a random sample of those who were originally at the military examination. It has been shown that in utero famine exposure increases mortality later in life(Ekamper et al., 2014, 2015). Other factors that influence both the administrative outcomes and survival such as parental background, also distort the representativeness of the sample and should, therefore, accounted for. Neglecting such selective survival may bias the estimation. In our analyses we will account for possible selective survival using either an inverse propensity weighting method or a Copula approach (Trivedi and Zimmer, 2007, Fan and Patton, 2014).

Another contribution of this study is that we are the first to investigate the impact of the Dutch famine on medication use and health expenditures later in life. Both health behaviors are classified by relevant categories. We distinguish medication prescriptions for diabetes, for cardiovascular diseases, for blood pressure, for hyperlipidemia, and for mental diseases. Health expenditures are distinguished by costs for general practitioners, for hospital visits, and for mental health. To acknowledge the dynamic nature of these health behaviors we focus on the changes over time of medication use and health expenditures. In all (including the labor market status) analyses we use a non-linear Difference-in-difference approach to identify the the causal impact of famine exposure in utero on later life outcomes.

In our empirical analyses we use administrative data on Dutch men who were examined for military service in the Netherlands between 1961-1965 after completing their secondary schooling. The military records include a standardized recording of demographic and socioeconomic characteristics along with a standardized psychometric test battery. These data were linked to the Dutch death register (till the end of 2014) and to other register data. We have access to monthly information of the labor market status (main source of income, observed from 1999 till 2013), including disability benefits and pensions, to annual personal income (observed 2003-2013), to annual prescribed medications (2006-2013), and to annual health expenditures (2009-2013).

2 Background of the Famine and Data

Prior to World War II, food standards had been high in the Netherlands, both in terms of caloric value as well as composition of the diet. There were no notable disruptions in food availability during the last years of the occupation of the Netherlands, which started in May, 1940. In September 1944, parts of the South of the country were liberated, and the London-based Dutch Government in exile called out a railroad strike in the occupied parts of the Netherlands as an attempt to display authority over the inhabitants of the occupied parts. In response, the occupying forces moved away the means of transportation from the occupied parts, effectively initiating an embargo on food transports to the densely populated western part of the country, i.e. the provinces of North and South Holland and in combination with the early onset of the harsh winter of 1944/45, the freezing of waterways, and the generally bad state of transport infrastructure, this effectively closed off the western part of the country from any imports of food, fuel, medication etc. This triggered the Dutch hunger winter. Individuals had to live on rations as low as 500 kcal per day. For school children, average rations amounted to 664 kcal in the first quarter of 1945. The situation lasted until the end of the occupation which coincided with the end of World War II (early May 1945).

Data from a large sample of men from the nationwide Dutch Military Service Conscription Register for the years 1961–1965 and born around the famine, 1944–1947, are analysed. All men, except those living in psychiatric institutions or in nursing institutes for the blind or for the deaf-mute, were called to a military service induction exam. The majority attended the conscription examination at age 18. We have information from the military examinations for 45,037 men. These individuals were originally sampled to study the relation between prenatal famine exposure and mortality (Ekamper et al., 2014). For this reason all the 25,283 men born in the Western Netherlands between November 1944 and March 1946 were included in the subsample. The remaining linked data are composed of a random sample of 10,667 individuals who were born in the same cities but before November 1944 or after March 1946, and a random sample of 9,087 individuals who were born in a different part of the Netherlands in 1944 − 1947. Details of the data are described elsewhere, Ekamper et al. (2014), here we provide the main characteristics. These data were linked to the Dutch death register through to the end of 2014 using unique personal identification numbers. Follow-up status was incomplete (due to emigration and other right-censoring events) for 1,316 (2.9%) and entirely unknown for 2,625 (5.8%) men. The latter were removed from the data. These data allow us to follow a large group of men from age 18 until age 71 or until death. At the military examination a standardized recording of demographic and socioeconomic characteristics such as date and place of birth, education, father's occupation, religion, family size, region of birth, and birth order is recorded.

To account for selective fertility, we only include individuals who were already conceived at the start of the famine. In other words, we exclude from the analysis everyone born after July 1945, just like Conti et al. (2019). We define three treatment groups: exposure starting in the first trimester (born May-July 1945), exposure starting in the second trimester (born February- April 1945), and exposure starting in the third trimester (born November 1944-January 1945). The control group includes those exposed only postnatally in the first months of life (born May-October 1944). We used the same selection criteria as Conti et al. (2019) for the control cities.

Thus, we have selected our control group of cities through the following steps. Given that the famine has historically affected more the cities, we have first restricted our sample of interest to the 46 municipalities with a population greater than 25,000 inhabitants on January 1, 1940. We have further excluded from this group, : (a) 4 municipalities where the majority of the population was not living in the largest place in the municipality (i.e. to be classified as rural not urban from their population dispersion pattern); (b) 13 municipalities where the population underwent major changes in size since 1930 (either increased more than 50% over the decade or had a decrease in the population after the onset of the war due to substantial population evacuations).

- *Famine cities*: Amsterdam, Delft, The Hague, Haarlem, Leiden, Rotterdam and Utrecht.
- *Control-cities*: Alkmaar, Almelo, Amersfoort, Apeldoorn, Bergen op Zoom, Bussum, Deventer, Dordrecht, Eindhoven, Gouda, Groningen, Heerlen, Helmond, Hengelo,'s Hertogenbosch, Kerkrade, Maastricht, Nijmegen, Roosendaal, Tilburg, Zaanstad, Zwolle

These data were linked to administrative data on the individual monthly labor market status, on individual annual income, on individual annual prescribed medications, and on individual annual insured health expenditures. Due to the original oversampling used for linkage to these administrative data, of men born in famine cities during the famine, the number of men born in the control cities in the linked data during this period is rather limited (only a few hundred).

Labour market dynamics

During the last four decades exiting from the labor force before the official retirement age of 65 has been quite common in the Netherlands. Up till the 1980s disability and unemployment were the main labor force exit routes for older workers, especially during periods of high unemployment (De Vos et al., 2012, Henkens, 1998). Receiving a disability benefit was both socially more acceptable and financially more attractive than receiving an unemployment benefit. Though several system reforms since the mid-1980s decreased the generosity of the disability (and unemployment) benefits, disability remained an attractive labor force exit route for a long time (De Vos et al., 2012). The first early retirement schemes in the Netherlands were introduced in 1976, mainly in reaction to rising unemployment, and gradually implemented by the various industrial sectors, covering around 75 per cent of the labor force end-1990s (De Vos et al., 2012, Henkens, 1998). Around 1980 about 60 per cent of the men aged 55-64 years were still working, 25 per cent in disability, and 9 per cent in early retirement. During the 1980s early retirement schemes started to become the most important exit route for older workers, partly caused by an overhaul of the system of social security in 1987 which made it more difficult for companies to lay off their older workers through disability or unemployment (De Vroome and Blomsma, 1991). But for those not entitled to early retirement, disability and unemployment – though less generous – remained early labor force exit routes (De Vos et al., 2012). Since 2000 some effective system reforms have been implemented to reduce the increasing costs of early retirement schemes and stimulate older workers to retire at later age; particularly the termination of tax exemption for early retirement contributions since 2006 (De Vos et al., 2012). The average (early) retirement age for men increased from 60 years in 2000-2006 to 61 in 2007 and since then gradually increased to 63.5 in 2015. Between 2000 and 2015 the percentage of the men aged 55-64 in early retirement and disability both declined from around 20 to 10 percent, the percentage still working increased from 42 to 62 per cent. Men from birth cohorts 1944-1947 reached age 60 years in the period 2004-2007 and official retirement age 65 years in the period 2009-2012.

Figure 1 depicts the development of labor market status by age. At age 52 more than 80% of the men are working, 9% is disabled, 5% is unemployed and 1% has already retired.

Figure 1: Development of labor market status by age

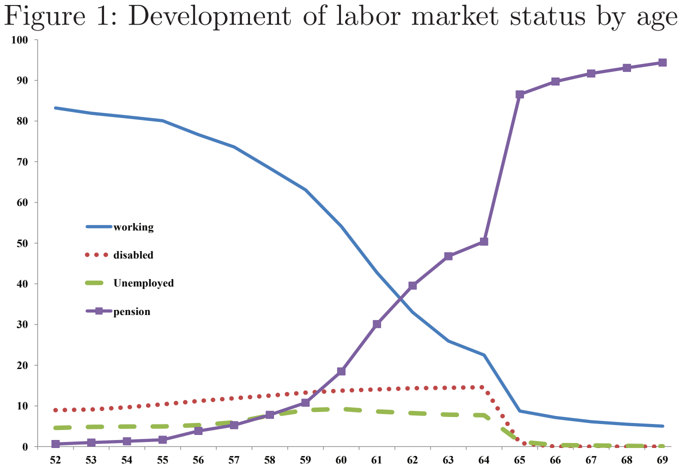
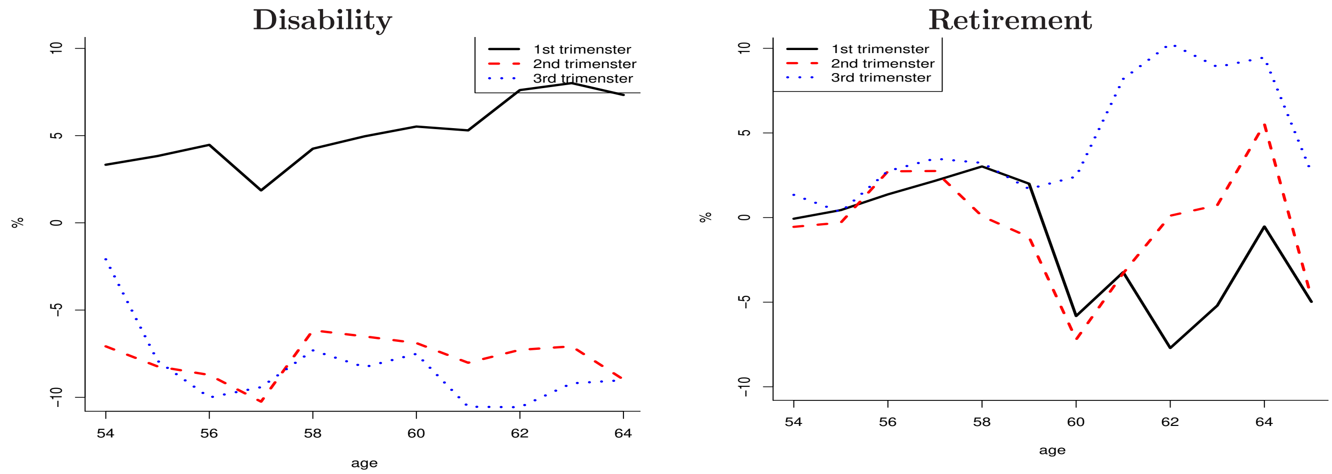


Figure 2 depicts the development of the difference in the disability and retirement prevalences between the famine cities and the control cities by gestation period and age.[1] Disability seems higher for those who were exposed to the famine in the first trimester of gestation and lower for those exposed in the second or third trimester of gestation. Retirement around age 60 seems lower for those exposed in the first and second trimester of gestation and retirement at age 62-64 seems higher for those exposed in the third trimester of gestation. Note that with selected control cities and fertility selection we only have a few men in each of the control groups.[2]

[1]Figure B.1 and Figure B.3 in Appendix B show the prevalences for the alternative selection criteria, with or without control city selection and with or without fertility selection. Figure B.2 and Figure B.4 in Appendix B show the differences in these prevalances between famine and control cities.

[2](1st trimester: 60; 2nd trimester: 95; 3rd trimester: 65), but much more in the famine cities (1st trimester: 3,785; 2nd trimester: 4,059; 3rd trimester: 4,032). When we do not impose the selected cities criterium we have 1st trimester: 402; 2nd trimester: 480; 3rd trimester: 384 observations. When we do not impose the fertility criterium we have 1st trimester: 141; 2nd trimester: 190; 3rd trimester: 160 observations (the observations in the famine cities also increase). When we do not impose any selection criterium we have 1st trimester: 862; 2nd trimester: 972; 3rd trimester: 864 observations in the control.

Figure 2: Difference in disability and retirement by famine region and gestation period



Notes. The upper panel depicts the difference in the prevalence of disability in the famine cities versus the control cities by gestation period and age. The lower panel depicts the difference in the prevalence of retirement in the famine cities versus the control cities by gestation period and age. We impose the fertility selection criterium and control cities selection.

Income

Negative health effects of the exposure to the famine may translate into disadvantageous socioeconomic outcomes, such as lower (labor) income. This impact of famine exposure can run through a direct effect of the famine exposure by impairments of cognitive ability or through a indirect effect of poor childhood health that both harm educational attainment and, subsequently, reduce labor market success. Results from Conti et al. (2019) indicate that the direct effect is likely to be more important as they find a robust famine exposure effect on BMI at age 18 for those exposed in early gestation, but no significant impact of famine exposure on mental health at age 18.

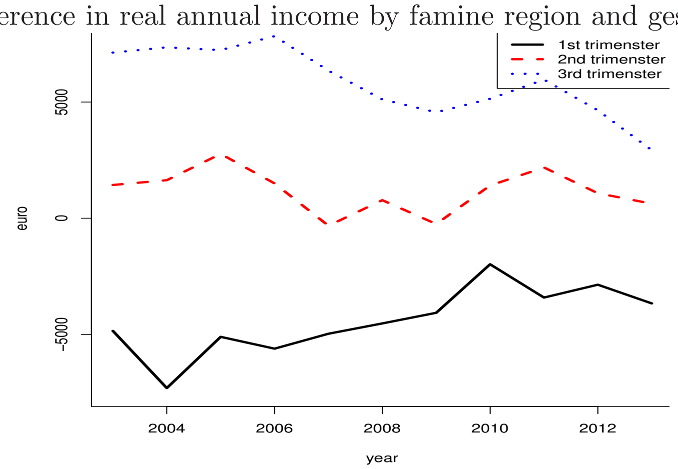
A few studies have investigated the long-run effect of famine exposure on (labor) income. Scholte et al. (2015) do not find any significant effect of exposure to the Dutch famine on labor income. Jürges (2013) finds the largest effects of the German famine (right after the end of WWII) for early pregnancy exposure on life-time earnings. Chen and Zhou (2007) find strong negative effects of exposure to the 1959-1961 famine in China on the annual per capita income of farmers.

We have access to the annual personal gross income for the years 2003-2013 in euro's and adjusted for inflation. Figure 3 depicts the development of the difference in (exponentiated of the average logarithm) income between the famine cities and the control cities by gestation period and year.[3]

We do not find any significant difference in the observed annual income for the famine exposed.

[3] Figure B.5 in Appendix B shows the real exponentiated income for the different selection criteria. Figure B.6 in Appendix B shows the differences in these incomes between famine and control cities.

Figure 3: Difference in real annual income by famine region and gestation period



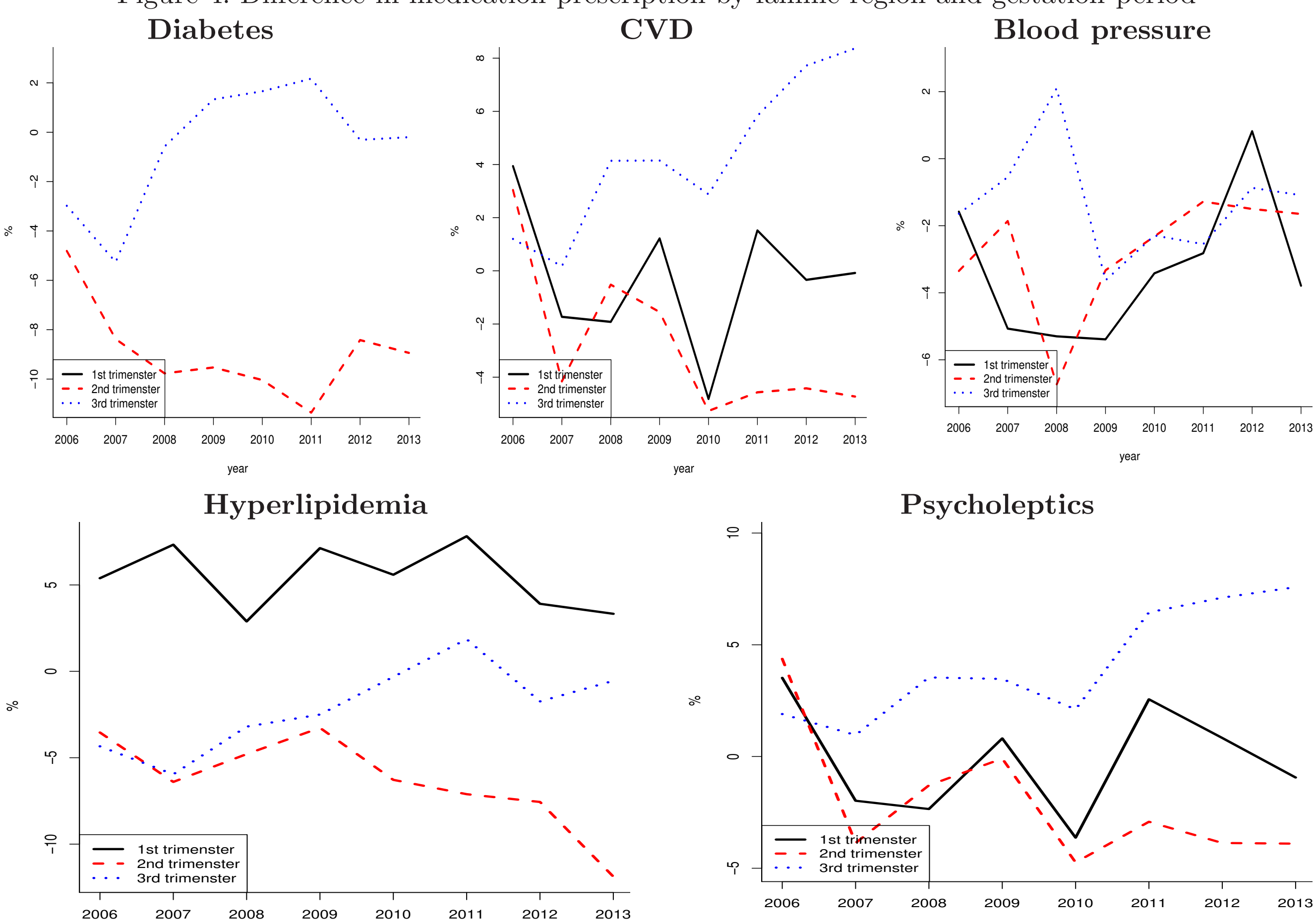
Notes. We impose the fertility selection criterium and control cities selection.

Medication use

Lumey et al. (2011) provided a review of studies on the association between prenatal famine exposure and health later in life, including blood pressure, lipid profile, cardiovascular outcomes and, mental outcomes. No association was found for any of these outcomes. Neither did Conti et al. (2019) find any significant impact of the famine on mental deficiency at age 18. Still, the *fetal-origins hypothesis* suggests a relation between famine expose in utero and later life health. We, therefore, re-investigate this relation by looking at medication use by older adults

We have access to prescribed medications on an annual basis in Anatomical Therapeutic Chemical (ATC) code and classified in three levels: the first indicates the anatomical main group, the second the therapeutic subgroup, and the third the pharmacological subgroup. We focus on five medications groups associated with (1) Diabetes; (2) Cardiovascular diseases (CVD); (3) blood pressure; (4) hyperlipidemia; and (5) psycholeptics. Figure 4 depicts the development of the difference in mediation prescription by famine region and gestation period for these five medication groups.

Figure 4: Difference in medication prescription by famine region and gestation period



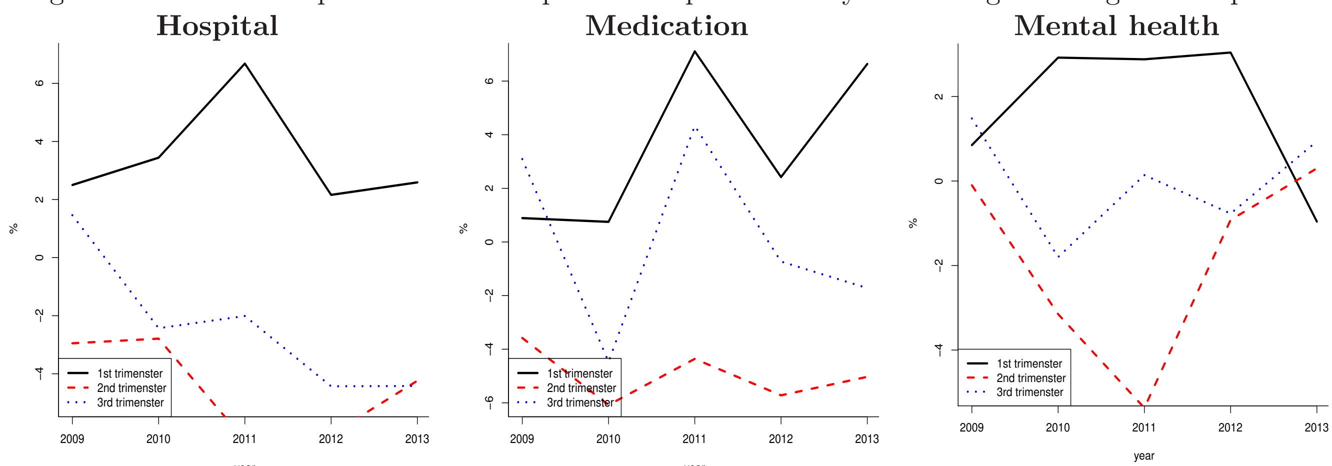
Notes. The panels depict the difference in the prevalence of medication prescription in the famine cities versus the control cities by gestation period and year. We impose the fertility selection criterium and control cities selection.

From the raw differences in medication use prevalence we get mixed results, both higher and lower medication use with famine exposure. Note that with using all controls and no fertility restriction we find for all, except blood pressure, higher medication use for the famine exposure cities for all gestation periods (see Figure B.8 in Appendix B).

Health expenditures

We have access to annual data on eight different health expenditures: costs classified by: general practitioner, pharmacy (medication use), dental, hospital, paramedical, medical aids, medical transportation and, mental costs. We focus on the costs for general practitioner (GP), pharmacy (medications), hospital visits and mental health. To account for asymmetrical distribution of health expenditures with many people with no expenditures and some with very large expenditures we look at the probability of positive health expenditures and at the (exponentiated) logarithm of the health expenditures.

Figure 5: Difference in positive health expenditures prevalence by famine region and gestation period

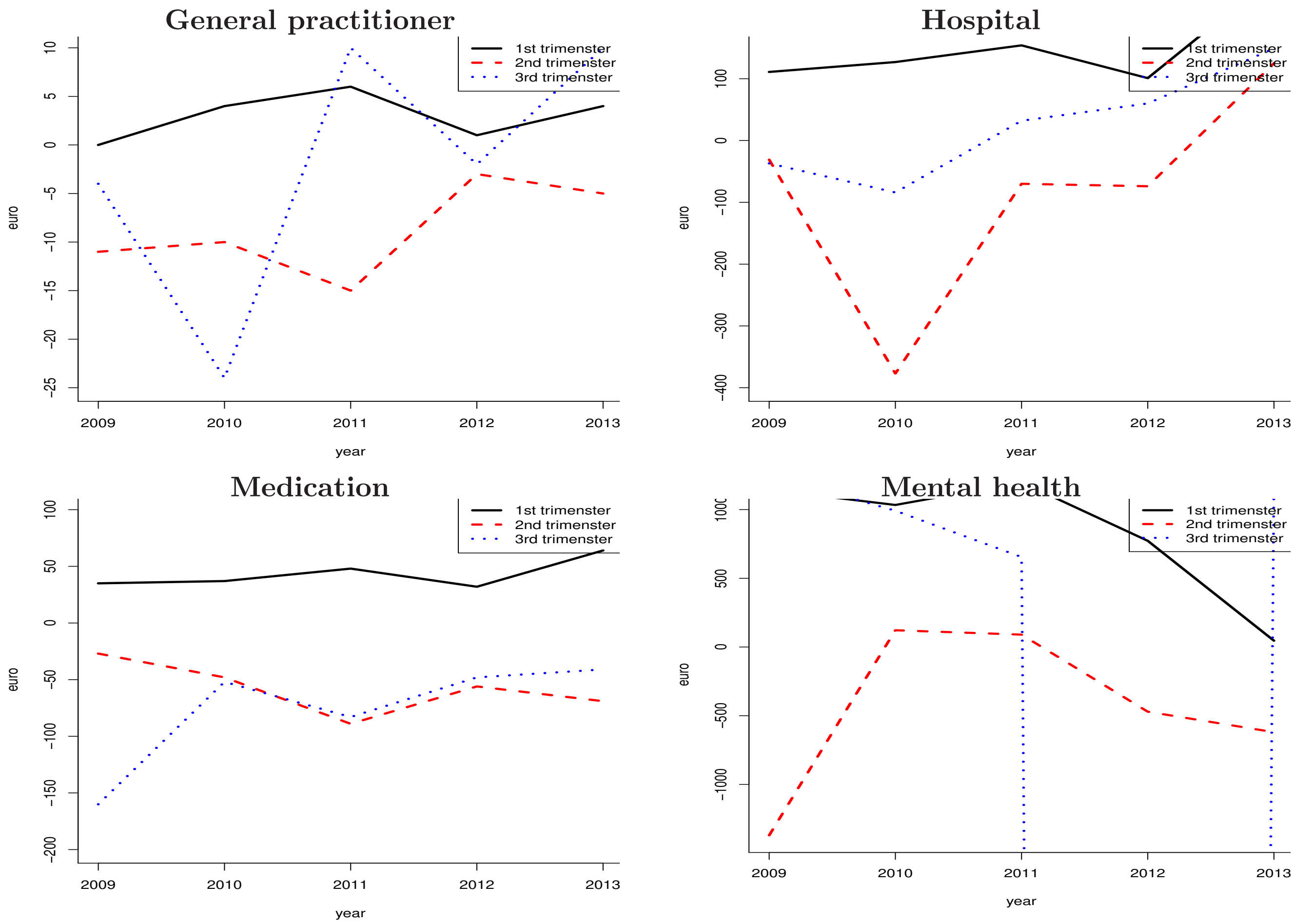


Notes. The panels depict the difference in the prevalence of positive health expenditures in the famine cities versus the control cities by gestation period and year. We impose the fertility selection criterium and control cities selection.

The raw differences indicate that exposure to the famine in the first gestation trimester increases the probability of having positive health expenditures (in 2010 and 2011). But exposure in the second or third trimester of gestation decreases this probability (Figure 5). The difference in total health expenditures between the famine exposed cities and the control cities is, however, never significant (Figure 6).[4]

[4]Figure B.9 and Figure B.11 in Appendix B for the the development of the the prevalence of positive health expenditures and the total health expenditures, for each expenditure category and by selection period. Figure B.10 and Figure B.12 in Appendix B depict the observed differences in both positive prevalence and total expenditure for each of the expenditure categories and for different selection criteria.

Figure 6: Difference in health expenditures by famine region and gestation period



Notes. The panels depict the difference in the health expenditures in the famine cities versus the control cities by gestation period and year. We impose the fertility selection criterium and control cities selection.

3 Methodology

We seek to find the impact of famine exposure in utero on different outcomes. For each outcome we formulate a different model, depending on the type of data. For each outcome we estimate the relevant Difference-in-Difference parameter of famine exposure in a particular gestation period.

3.1 Labor market transitions

We will employ survival models for the timing (the age at departure) of disability and retirement transitions. Our two main outcome measures are the disability- and retirement hazard, $\lambda(t)$. We model these hazards using a proportional hazard model:

$$\lambda(t|X) = \lambda_0(t)\exp(\beta X + \alpha F + \gamma T + \theta F \cdot T) \tag{1}$$

The baseline hazard (the age-dependence) is either Gompertz, exponentially growing, for the (early) retirement hazard (after age 50) or a piecewise constant baseline hazard on seven intervals (younger than 39 as reference, 39-40, 40-41, 41-42, 42-43, 43-46 and older than 46) for the disability hazard (after age 18).

To account for possible secular trends and differences between the famine cities and control cities in The Netherlands we use a Differences-in-differences (DID)-approach for obtaining the impact of the famine exposure by using time-dummies T (using three different exposure periods), a place indicator, F (exposed cities in the West) and the interaction of these two $F \cdot T$ to identify the impact of the famine on the hazard rate. The hazard rates are inherently non-linear and the standard DID does not hold. Puhani (2012) derived a non-linear DID can be obtained by

$$\text{DID}(t) = \lambda_0(t)\exp(\alpha + \gamma + \theta + \beta X) - \lambda_0(t)\exp(\alpha + \gamma + \beta X) \tag{2}$$

Note that the effect depends on age, t, as the baseline hazard is changing with age and on the value of the control variables X. We will calculate the DID(t) for the average individual, i.e. $X = \bar{X}$.

Some of the men have already entered disability (9%) or retirement (1%) at the first observation time, 1-1-1999. Such left-truncation can easily be handled in (parametric) hazard rate models, by dividing the likelihood by the probability of such an event. Using the parametric model we have an explicit formula for the probability of having such an event, $\Pr(\text{left} - \text{truncation}) = 1 - \exp\big(-\int_0^{t_{99}} \lambda(s|X)\, ds\big)$ with t_{99} is the age at 1-1-1999 and given the hazard function in (1).

3.2 Income

Individual income in one particular year depends on the income the year before. Thus, there is a strong dynamic correlation in income. This dynamic correlation could either stem from unobserved heterogeneity (e.g. high ability) and/or from true state dependence (e.g. people experienced in period $t-1$ an income shock which could turn out to be very persistent). But the income level may also be persistent for other reasons. Exposure to famine early in may predispose an individual to lower income levels that linger over time. Based on the observations made above, we postulate the following dynamic model for (the logarithm of) income.

$$y_{it} = \beta_y y_{i,t-1} + \beta_x' x_i + \alpha F + \gamma T + \theta F \cdot T + \beta_t + \eta_i + \epsilon_{it} \qquad i = 1, \dots, N; \quad t = 2, \dots, T \tag{3}$$

where $y_{i,t-1}$ is the lagged value of (log) income, x_i is a vector of time invariant regressors (measured at age 18), β_t is a period effect (the year of observation), η_i is an unobserved individual effect capturing unobserved heterogeneity and ϵ_{it} denote a unit mean normally distributed (with variance σ^2), serially uncorrelated error term assumed to be independent of x_i. We include lagged income in model (3) to capture true state dependence.

A common issue with dynamic panel data models is correlated unobserved heterogeneity (the initial conditions problem). We use the suggestion of Wooldridge (2005) which approximates the density of η_i conditional on the initial observation $y_{i,1}$ and x_i (see also Skrondal and Rabe-Hesketh (2014)):

$$\eta_i \approx \xi_y y_{i,1} + \xi_x' x_i + \alpha_\eta F + \gamma_\eta T + \theta_\eta F \cdot T + \omega_i \tag{4}$$

where $\omega_i \sim \mathcal{N}(0, \sigma^2)$ independent of $y_{i,1}$ and x_i and the . Substitution of equation (4) into (3) yields

$$y_{it} = \tilde{\beta}_y y_{i,t-1} + \tilde{\beta}_x' x_i + \tilde{\alpha} F + \tilde{\gamma} T + \tilde{\theta} F \cdot T + \beta_t + \omega_i + \epsilon_{it} \qquad i = 1, \ldots, N; \quad t = 2, \ldots, T \tag{5}$$

where $\tilde{\beta} = \beta + \xi, \tilde{\alpha} = \alpha + \alpha_\eta, \tilde{\gamma} = \gamma + \gamma_\eta$ and $\tilde{\theta} = \theta + \theta_\eta$.

Using Puhani (2012) again we derive a non-linear DID for the exponentiated log-income with normal distributed errors.

$$\text{DID} = \exp(\tilde{\alpha} + \tilde{\gamma} + \tilde{\theta} + \tilde{\beta}_y Y + \tilde{\beta}_x \bar{X} + \tfrac{1}{2}\sigma^2) - \exp(\tilde{\alpha} + \tilde{\gamma} + \tilde{\beta}_y Y + \tilde{\beta}_x \bar{X} + \tfrac{1}{2}\sigma^2) \tag{6}$$

Note that is equal to the marginal effect of exposure to the famine, $F \cdot T$, on the expected exponentiated log-income conditional on one of the three gestation periods and born in a famine city (and the average value of all the other included variables).

3.3 Prescribed medications

Most likely, there is also a strong dynamic correlation in prescribed medication, either due to unobserved heterogeneity (e.g. illnesses could be inherently chronic and long lasting) and/or due to true state dependence (e.g. people experienced in period $t-1$ a health shock which could turn out to be very persistent). We therefore estimate a dynamic probit model for the prescribed medications,

$$m_{it}^* = \beta_m m_{i,t-1} + \beta_x' x_i + \alpha_m F + \gamma^m T + \theta^m F \cdot T + \beta_t^m + \eta_i^m + \epsilon_{it}^m \qquad i = 1, \ldots, N; \quad t = 2, \ldots, T \tag{7}$$

where m_{it}^* represents a latent variable of the medication use indicator $m_{it} = I\big(m_{it}^* > 0\big)$, using again the Wooldridge (2005) suggestion to solve the initial conditions problem (see (4)).

Based on this dynamic probit model we derive the relevant DID famine impact by using Puhani (2012) again, which is the marginal effect of exposure to the famine on the medication prescription conditional on one of the three gestation periods and born in a famine city.

3.4 Health expenditures

Most economic analyses of health expenditures have adopted the two-part model (Mullahy, 1998, Smith et al., 2017). A two-part model treats the probability of positive expenditures and the expected expenditures conditional on positive expenditures separately. It assumes that the probability of positive expenditures is governed by a binary probability model like a probit or logit and a conditional regression model for the positive expenditures. Health expenditures data are usually heavily skewed and exhibit excess kurtosis. Empirical applications of the two-part model for health expenditures have often used logarithmic transformation to account for this. For each health expenditure category we use a probit model for the probability of positive health expenditures and a log-linear regression with normal distributed errors for the health expenditure.

Again we assume possible dynamic correlation for both parts of the model, the probability of positive health expenditures and the log-health expenditures. Again we use the Wooldridge (2005) suggestion to solve the initial conditions problem, see the previous sections. We also allow for interdependence of the probability of positive health expenditures and the log-health expenditures by assuming a bivariate normal distribution for the error terms.

Based on this model we derive, for each health expenditure category, three alternative DID impacts of famine exposure: (*i*) the impact on the probability of positive health expenditure; (*ii*) the impact on the total health expenditure; (*iii*) the impact on the health expenditure conditional on positive expenditures. For all three famine impacts we use Puhani (2012) again. The first famine impact is the marginal effect of exposure to the famine on the probability of positive health expenditure (see Section 3.3), the second is the marginal effect of exposure to the famine on the the expected exponentiated log-health expenditure and, the third is the marginal effect of exposure to the famine on the the expected exponentiated log-health expenditure for those with a positive health expenditure (of course all conditional on one of the three gestation periods and born in a famine city).

3.5 Selective survival

The men who survive till the date of the first observation of the outcomes, 1999 (labor)- 2009 (health expenditures), may be a selective sample of those investigated at the military examination. It has been shown that exposure to the famine increases mortality later in life (Ekamper et al., 2014, 2015). Other factors that influence the outcome may also affect mortality, e.g. father's occupation and family size. Neglecting such selective survival may bias the estimated impact of the famine on the outcomes.

Inverse propensity weighting

One way to account for this is to weight each individual observation with the probability of surviving till 1^{st} January of the first observation year of the outcome.[5] Such an Inverse Propensity Weighting (IPW) method effectively creates a sample that is independent of the survival. To this end we first estimated a Gompertz Mixed Proportional hazard model, with a discrete unobserved heterogeneity distribution, for the survival using all the controls and the famine exposure indicators as explanatory variables for the selected sample, born in the famine cities or the selected control cities before August 1945 (results are available upon request). Based on this model we calculate for each individual the probability to survive till 1^{st} January of the first observation year of the outcome. The IPW method weights each observation (of those still alive after 1^{st} January of the first observation year of the outcome) by the inverse of this survival when estimating the different models.

Copula approach

A drawback of the IPW method is that it assumes unconfoundedness, no selection on unobservables. The unconfoundedness assumption (Rosenbaum and Rubin, 1983) asserts that, conditional on (early-life) covariates X, survival is independent of the outcomes. This assumption requires that all variables that affect both the outcome and survival till the first observation of this outcome are observed. This may be a very restrictive assumption. Unfortunately, the unconfoundedness assumption is unrefutable without additional data.

We will use Copula models to account for selection on unobservables. The use of Copulas to account for selection was first introduced by (Smith, 2003). In a copula approach the joint distribution of, in our case, the outcome (possibly two for the two-part models for health expenditures) and survival, is induced by the marginal distributions and a function that links them together, the copula (Trivedi and Zimmer, 2007, Fan and Patton, 2014). The copula parameter governs the degree of dependence between the marginals.

[5] 1999 for labor market transitions, 2003 for income, 2006 for medication prescriptions and 2009 for health expenditures.

For the dynamic models for income, medication use and health expenditures we assume a Gaussian copula, which implies adding an additional (survival) equation to the model that is (possibly) correlated to the other equation(s) by assuming a multivariate normal error distribution. Note that this survival model is not dynamic, as non-survival is a terminal event.

For the hazard rate model of labor market transitions we assume a Clayton copula model, that is common for survival analysis (Georges et al., 2001). The latter model is described in more detail in Appendix A.

4 Results

4.1 Labor market status

For comparison with Scholte et al. (2015) who look at the impact of the famine on the employment probability, we start with a simple analysis of the labor market status at 1999 and how it is affected by famine exposure. Table 1 reports the results. The first three panels give the observed labor market status on 1-1-1-1999 by gestation period and famine exposure (imposing the fertility selection and selection of control cities[6]) and the implied difference. Note that the percentages add up to more than 100%, as people may be both working and receiving benefits. The final panel of Table 1 presents the DID estimate of famine exposure on the labor market status on 1-1-1999 using a linear probability models with a DID structure . We do not find any significant impact of the famine on the labor market status on 1-1-1999.

Table 1: Labor market status in 1999 by famine exposure period: famine cities vs control

	working	disabled	unemployed	retired
	Famine cities, $N = 12,873$			
1st trimester	82.50%	15.14%	8.20%	5.78%
2nd trimester	83.99%	14.55%	7.94%	4.98%
3rd trimester	84.09%	13.82%	7.80%	5.46%
	control cities, $N = 391$			
1st trimester	79.66%	8.47%	8.47%	6.78%
2nd trimester	75.53%	23.40%	10.64%	6.38%
3rd trimester	72.31%	24.62%	10.77%	6.15%
	difference			
1st trimester	2.84%	6.67%	−0.27%	−1.00%
2nd trimester	7.48%	−8.85%	−2.68%	−1.40%
3rd trimester	11.78%	−10.80%	−2.97%	−0.69%
	DID[a]			
1st trimester	0.26%	10.14%	−1.26%	−0.99%
2nd trimester	5.03%	−4.65%	−3.28%	−1.66%
3rd trimester	9.38%	−6.89%	−4.05%	−1.16%

[a] Difference-in-difference estimation with included controls: Province of birth dummies, number of older brothers, religion dummies, father's occupation (6 cat.), trend and trend squared *Full selection*: only control cities, born May 1944- July 1945

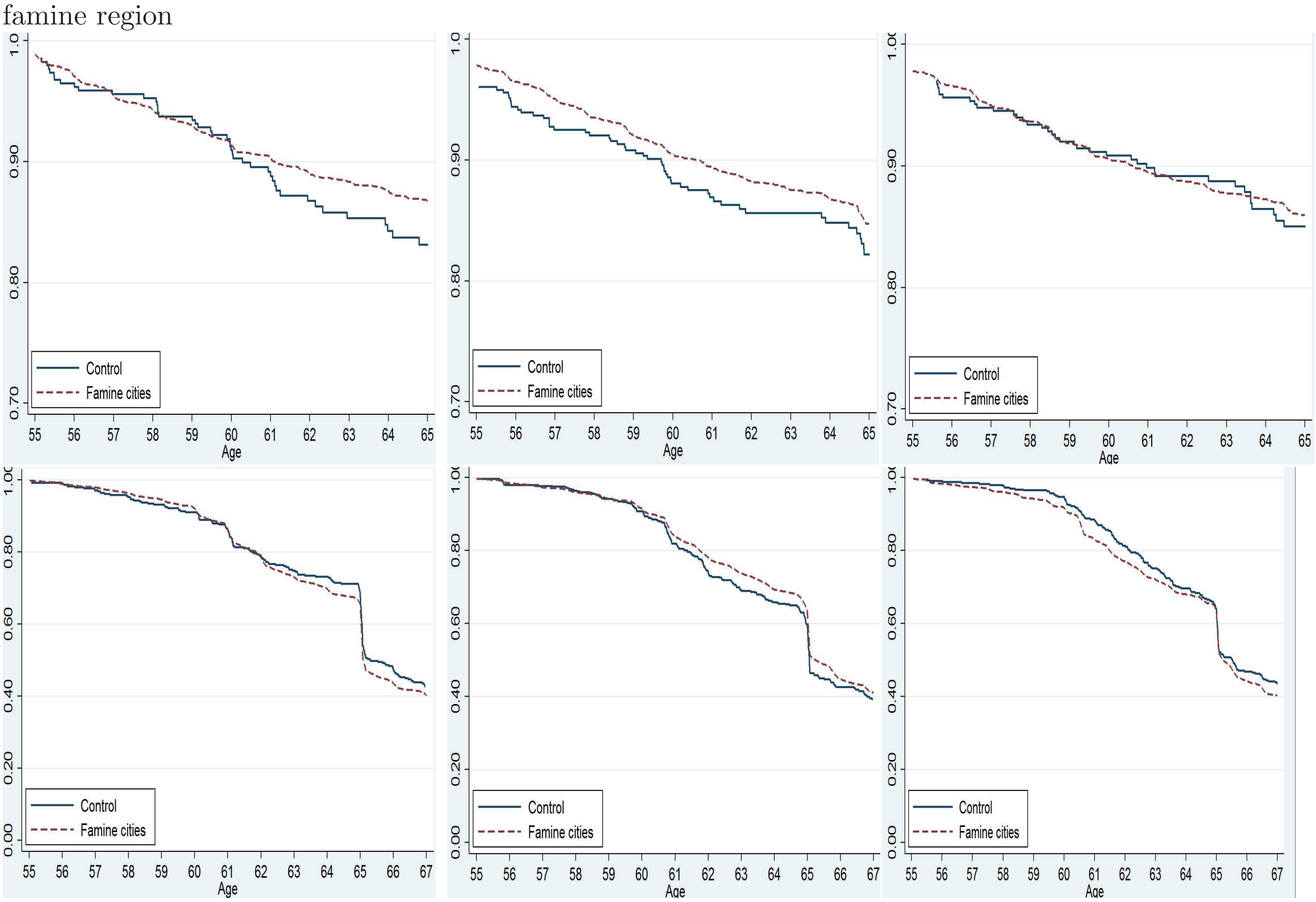
In contrast to the approach taken by Scholte et al. (2015), we will not look at the impact of the famine on the employment probability further, but focus on the impact of the famine on the timing

[6]The observed differences and simple DID estimate for alternative selection criteria are presented in Table B.1 in Appendix B.

of becoming disabled or retired (see Section 3.1). This is essential as the probability of occupying a particular employment state at a particular time ignores the dynamic nature of labor market changes. These two labor market states are clearly influenced by health. We do not consider (un)employment entry and departure as these labor market dynamics depend heavily on the labor market history from the start at the labor market and we only start observing these men when they are between age 52 (born in 1947) and age 55 (born in 1944).

We start with a simple non-parametric analysis of the timing of these labor market transitions, the Kaplan-Meier survival curves. Figure 7 depicts these survival curves by famine region and famine exposure period. The timing of disability for those exposed to the famine in the second trimester of gestation seems higher.

Figure 7: Kaplan-Meier survival curves for time till disability or retirement, by gestation period and famine region



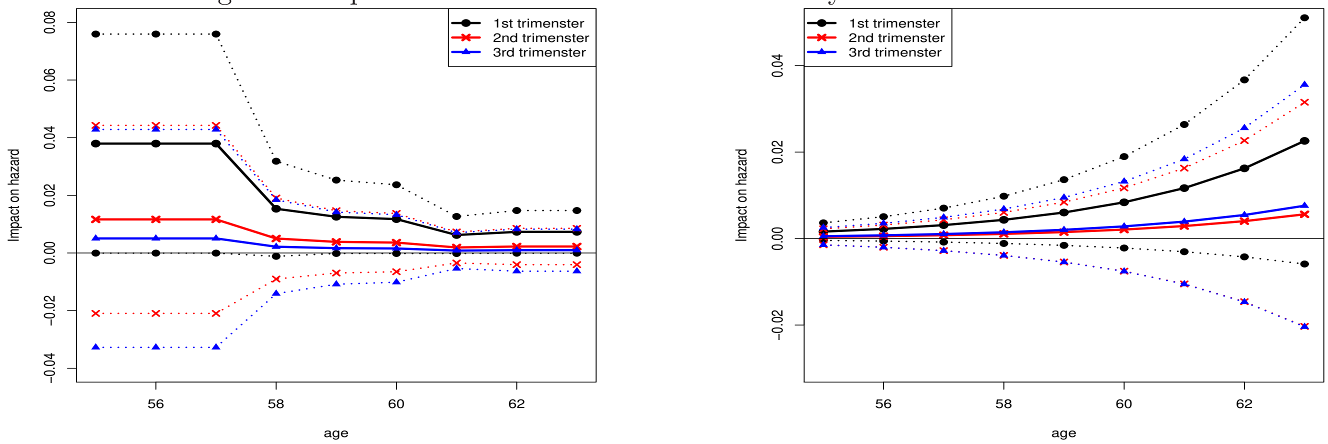
3rd **trimester** 2nd **trimester** 1st **trimester**

Notes: The upper panels depict the survival curves of the time till disability and the lower panels of the time till retirement. 3rd trimester, born November 1944- January 1945; 2nd trimester, born February 1945 - April 1945; 1st trimester, born May 1945 - July 1945.

Figure 8 presents the estimated impact of the famine for the three exposure trimesters for disability and retirement.[7] We find a positive, but statistically insignificant, impact of the famine on the timing of disability and (early) retirement.

[7]The estimated impact of the famine for other selection choice can be found in in Figure B.13 in Appendix B.

Figure 8: Impact of famine on the annual disability and retirement hazard

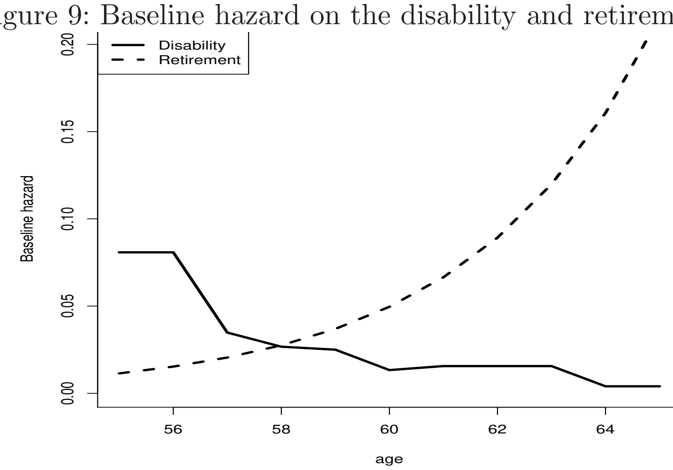


Disability **Retirement**

Notes: Impact in change of annual hazard rate. The dotted lines are the 95% confidence bounds.

For comparison we also present the (estimated) baseline hazard of becoming disabled and early retirement in Figure 9. The incidence of disability decreases with age and the incidence of early retirement increases with age.

Figure 9: Baseline hazard on the disability and retirement

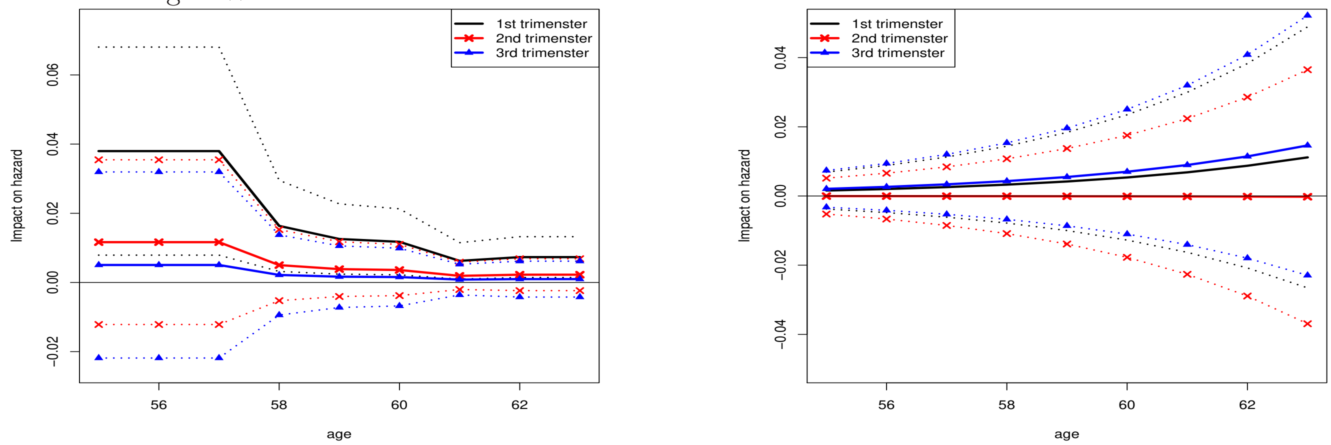


Selective survival

Next we account for (possible) selective survival till 1999 using either an IPW method with weights based on the estimated survival function or a Copula approach with a Clayton Copula, see Section 3.5. Figure 10 presents the estimated impact of the famine for the three exposure trimesters for disability and retirement when accounting for selective survival using an IPW method. It shows that after accounting for survival exposure to the famine in the first trimester of gestation (statistically significant) accelerates the timing of disability later in life. The impact of the famine on the timing of retirement remains statistically insignificant.

The estimated impact of famine exposure on the timing of disability and retirement when accounting for selective survival using a Clayton copula are very close (although with a different sign for the first and second trimester) to the results with IPW correction, see Figure 11. Again we find that only famine

Figure 10: Impact of famine on the annual disability and retirement hazard, accounting for selective survival using IPW

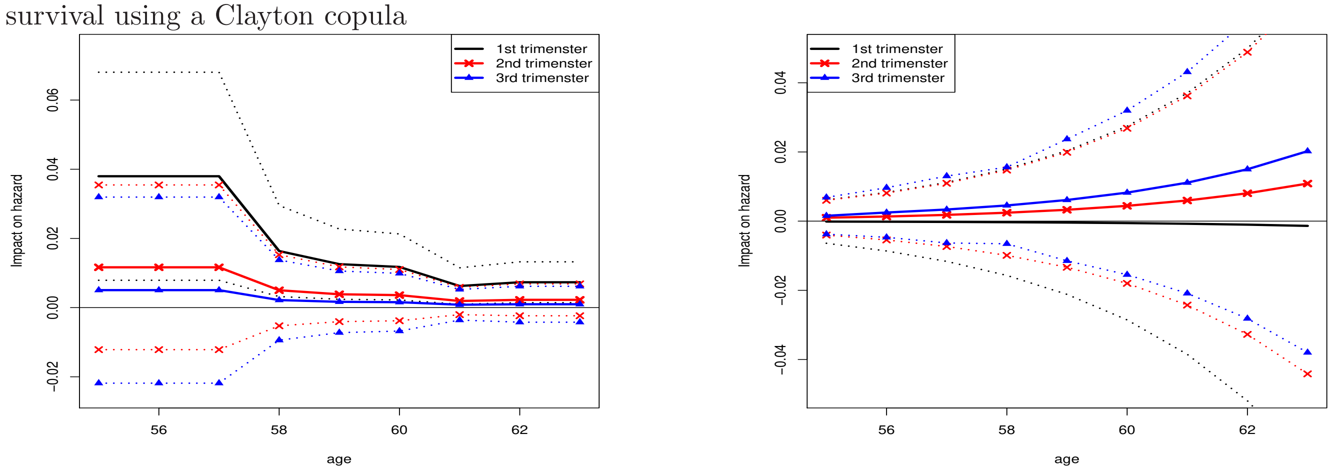


Disability **Retirement**

Notes: Impact in change of annual hazard rate. The dotted lines are the 95% confidence bounds.

exposure in the first trimester of gestation affects labor market transitions, by increasing the disability hazard later in life.

Figure 11: Impact of famine on the annual disability and retirement hazard, accounting for selective survival using a Clayton copula



Disability **Retirement**

Notes: Impact in change of annual hazard rate. The dotted lines are the 95% confidence bounds.

4.2 Income

Next we investigate whether personal income later in life is affected by famine exposure. We use the dynamic model described in Section 3.2 and look at the DID impact of famine exposure on personal annual income We check how the choice of the control cities and the famine exposure affects the results. Table 2 presents the estimated DID impact of the famine using different selection criteria. We find that famine exposure negatively affects labor income (imposing both fertility and control city selection).

Table 2: DID Impact of famine on real annual income

	DID[b]	control mean[b]	% difference[b]
		all[a]	
1st trimester	-€ 363^{+}	€ 33,914	-1%
2nd trimester	-€ 277	€ 33,355	-1%
3rd trimester	-€ 67	€ 33,777	-0%
		Control cities[a]	
1st trimester	-€ 735	€ 36,966	-2%
2nd trimester	-€ 140	€ 34,194	-0%
3rd trimester	€ 228	€ 33,884	1%
		Fertility[a]	
1st trimester	-€ 211	€ 32,035	-1%
2nd trimester	-€ 169	€ 32,355	-1%
3rd trimester	€ 246	€ 30,284	1%
		Full selection[a]	
1st trimester	-€ 950	€ 38,234	-2%
2nd trimester	-€ 624	€ 33,489	-2%
3rd trimester	€ 520	€ 29,035	2%

[a] *all*: all controls, using whole period 1944-1947; *Control cities*: only control cities, using whole period; *Fertility*: all control born May 1944- July 1945; *Full selection*: only control cities born May 1944- July 1945

[b] DID: estimated DID; control mean: mean income 2003-2013 for those born in the control region for the given gestation period; % difference: DID as % of control mean.

Included controls: Province of birth dummies, number of older brothers, religion dummies, father's occupation (6 cat.), trend and trend squared. $^{+}p < 0.05,^{**} p < 0.01$.

Table 3 presents presents the estimated DID impact for the analysis that account for selective survival till 1-1-2003 using either IPW with weights based on the estimated survival function or a Gaussian Copula(see Section 3.5). Accounting for selective survival using the IPW or the Copula approach hardly affects the effect of famine exposure on income later in life. Still, we do not find any significant effect of famine exposure.

Table 3: DID Impact of famine on annual real income, accounting for selective survival (using full selection for control cities)

	DID[b]	control mean[b]	% difference[b]
		IPW[a]	
1st trimester	-€950	€38,234	-2%
2nd trimester	-€622	€33,489	-2%
3rd trimester	€518	€29,035	2%
		Copula[a]	
1st trimester	-€948	€38,234	-2%
2nd trimester	-€620	€33,489	-2%
3rd trimester	€517	€29,035	2%

[a] *IPW*: Inverse probability weighting correction for survival till 2003; *Copula*: Joint, copula, distribution for survival till 2003

[b] DID: estimated DID; control mean: mean income 2003-2013 for those born in the control region for the given gestation period; % difference: DID as % of control mean.

Included controls: Province of birth dummies, number of older brothers, religion dummies, father's occupation (6 cat.), trend and trend squared. $^{+}p < 0.05$, $^{**}p < 0.01$.

4.3 Prescribed medication

If famine exposure affects health later in life it would increase medication use. We check this using data on annual medication prescription (distinguishing medication by the 4-level Anatomical Therapeutic Chemical Classification System, ATC-code) 2006-2013. We use the dynamic probit model described in Section 3.3 and look at the DID impact of famine exposure. The results reported in Table 4 indicate that prescription of none of the considered medications is affected (statistically significant) by famine exposure when imposing both fertility and control city selection. However, we do find a few statistically significant effects of famine exposure with a less restrictive sample choice.

Table 4: Impact (change in percentage) of famine on the probability of prescribed medication (DID)

	all[a]		control cities[a]		fertility[a]		full selection[a]	
	DID[b]	control mean[b]	DID[b]	control mean[b]	DID[b]	control mean[b]	DID[b]	control mean[b]
				Diabetes medication				
1^{st} trimester	−0.02	10.15	−0.24	10.96	−0.29	9.80	−0.21	8.68
2^{nd} trimester	0.17	10.88	−0.50	17.53	−0.01	12.77	−0.98	21.84
3^{rd} trimester	0.08	10.38	0.25	11.37	−0.06	10.35	−0.28	11.83
				CVD medication				
1^{st} trimester	0.46	37.71	0.36	39.73	0.67	42.15	0.55	46.29
2^{nd} trimester	0.01	39.99	−0.05	41.60	0.26	42.94	0.15	47.48
3^{rd} trimester	0.58	38.47	1.11	36.74	1.30^{+}	40.33	2.41	39.66
				Blood pressure medication				
1^{st} trimester	0.23	3.77	−1.22	5.98	−0.64	3.86	−2.00	7.89
2^{nd} trimester	−0.08	4.82	−0.28	4.54	−0.90	4.89	−0.70	7.09
3^{rd} trimester	0.23	3.80	−0.52	5.14	−0.52	3.33	−0.92	5.40
				Lipid medication				
1^{st} trimester	0.66	26.49	1.81^{+}	24.94	0.64	29.82	1.19	26.96
2^{nd} trimester	0.68^{+}	29.61	−0.33	32.61	−0.02	33.48	−1.66	38.26
3^{rd} trimester	0.36	26.98	0.22	30.10	0.73	26.96	0.64	32.95
				Psycholeptics medication				
1^{st} trimester	0.37	37.22	0.44	38.59	0.85	41.51	0.62	44.50
2^{nd} trimester	0.12	39.10	0.08	40.43	0.37	42.35	0.11	46.09
3^{rd} trimester	0.52	38.04	1.09	35.41	1.31^{+}	40.61	2.25	39.14

[a] *all*: all controls, using whole period 1944-1947; *Control cities*: only control cities, using whole period; *Fertility*: all control born May 1944- July 1945; *Full selection*: only control cities born May 1944- July 1945
[b] DID: estimated DID; control mean: mean medication use prevalence 2006-2013 for those born in the control region for the given gestation period;
Included controls: Province of birth dummies, number of older brothers, religion dummies, father's occupation (6 cat.), trend and trend squared. $^{+}p < 0.05,^{**} p < 0.01$.

We also account for selective survival till 2006 using either IPW with weights based on the estimated survival function or using a Gaussian Copula (see Section 3.5). Table 5 shows that also after accounting for selective survival famine exposure does not (statistically significant) affect medication use later in life. The only exception is that with a Copula approach we find a statistically significant positive impact of famine exposure on psycholeptics medication use. The men exposed to the famine in the third trimester of gestation have 4.2%-point higher prevalence of psycholeptics use.

Table 5: Impact (in percentage) of famine on the probability of prescribed medication (DID), accounting for selective survival

	IPW[a]	Copula[a]	control mean[a]
	Diabetes medication		
1st trimester	−0.21	−0.16	8.68
2nd trimester	−0.98	−0.94	21.84
3rd trimester	−0.28	−0.01	11.83
	CVD medication		
1st trimester	0.56	0.49	46.29
2nd trimester	0.15	0.15	47.48
3rd trimester	2.41	2.18	39.66
	Blood pressure medication		
1st trimester	−2.01	−1.71	7.89
2nd trimester	−0.70	−0.28	7.09
3rd trimester	−0.92	0.14	5.40
	Lipid medication		
1st trimester	1.19	0.74	26.96
2nd trimester	−1.66	−3.49	38.26
3rd trimester	0.64	−1.11	32.95
	Psycholeptics medication		
1st trimester	0.63	1.07	44.50
2nd trimester	0.11	0.30	46.09
3rd trimester	2.25	4.22^{+}	39.14

[a] *IPW*: DID with Inverse probability weighting correction for survival till 2003; *Copula*: DID after joint copula, distribution for survival till 2003; control mean: mean medication use prevalence 2006-2013 for those born in the control region for the given gestation period;
Included controls: Province of birth dummies, number of older brothers, religion dummies, father's occupation (6 cat.), trend and trend squared. $^{+}p < 0.05,^{**} p < 0.01$.

4.4 Insured health expenditures

Another measurement related to health impairment is the amount of individual health expenditures. We have access to data on annual insured health expenditures 2009-2013 and we only focus on expenditures on general practitioner (GP), hospital, medication costs and mental costs. We estimate the dynamic two-part model for each health expenditure category as described in Section 3.4 and calculate the implied DID effect of famine exposure. In Table 6 we report the impact of famine exposure on the probability of (positive) health expenditure and in Table 6 the impact of famine exposure on the amount of health expenditure. Imposing full selection renders the impact of famine exposure on health expenditure prevalence statistically insignificant for all gestation periods for all expenditure categories (the general practitioner expenditures is not considered, because virtually all men have positive GP expenditures). We find a few significant results of famine exposure on medication use for less restrictive sample selection.

Famine exposure statistically significant affects the total expenditure spend on medication (lower expenditure if exposure in the second trimester of gestation) and on mental health (higher expenditure if exposure in first or third trimester of gestation).

Table 6: Impact (in percentage) of famine exposure on the probability of positive health expenditure

	all[a]		Control cities[a]		Fertility[a]		Full selection[a]	
	DID[b]	control mean[b]	DID[b]	control mean[b]	DID[b]	control mean[b]	DID[b]	control mean[b]
					Hospital			
1[st] trimester	0.64	74.55	1.87	75.21	1.93	75.17	3.23	74.94
2[nd] trimester	−0.44	76.61	0.81	75.01	0.18	78.10	−1.03	80.34
3[rd] trimester	1.17	72.22	−0.30	76.29	2.34	74.41	−1.26	79.11
					Medications			
1[st] trimester	−0.09	83.44	1.49	82.50	0.04	84.73	4.24	81.89
2[nd] trimester	−0.54	84.52	0.82	82.29	-0.25^{**}	85.96	−0.80	90.07
3[rd] trimester	0.04	82.48	0.72	84.09	0.45^{+}	83.45	0.46	84.43
					Mental			
1[st] trimester	5.79	2.45	16.96^{+}	1.49	7.36	2.55	14.98	1.16
2[nd] trimester	−1.00	2.67	−3.29	2.85	2.64	3.11	−3.54	5.23
3[rd] trimester	−0.34	2.27	1.71	1.91	3.81	2.35	−1.22	3.05

[a] *all*: all controls, using whole period 1944-1947; *Control cities*: only control cities, using whole period; *Fertility*: all control born May 1944- July 1945; *Full selection*: only control cities born May 1944- July 1945

[b] DID: estimated DID; control mean: mean positive health expenditures prevalence 2009-2013 for those born in the control region for the given gestation period;

Included controls: Province of birth dummies, number of older brothers, religion dummies, father's occupation (6 cat.), trend and trend squared. $^{+}p < 0.05$, $^{**}p < 0.01$.

These results hardly change when we account for selective survival till January 2009 using an IPW method, see Table 8. But, when we use a Copula approach we do find some small differences in the obtained impact of famine exposure on expenditures given positive expenditures. For medications expenditures a Copula correction for selective survival implies that famine exposure in the second trimester of gestation reduces (statistically significant) these conditional expenditures and famine exposure in the first trimester of gestation is not statistically significant anymore. For mental health expenditures a Copula correction implies that the conditional expenditures statistically significant increases if exposed to the famine in the first trimester of gestation.

Table 7: Impact of famine exposure on amount of health expenditures in euro's per year

	General practitioner		Hospital		Medications		Mental health	
	DID[b]	control mean[b]	DID[b]	control mean[b]	DID[b]	control mean[b]	DID[b]	control mean[b]
	total expenditures							
	all[a]							
1st trimester	-€ 1.0	€ 152	-€ 73	€ 2265	€ 12	€ 729	-€ 236	€ 39
2nd trimester	-€ 2.0	€ 152	€ 127	€ 1954	-€ 14	€ 542	-€ 88	€ 49
3rd trimester	€ 1.8	€ 149	€ 316^{+}	€ 2009	€ 5	€ 484	€ 489	€ 64
	Control cities[a]							
1st trimester	€ 0.2	€ 152	-€ 54	€ 2265	€ 8	€ 729	-€ 651	€ 39
2nd trimester	-€ 1.8	€ 152	€ 181	€ 1954	-€ 44	€ 542	-€ 1520	€ 49
3rd trimester	€ 1.5	€ 149	-€ 174	€ 2009	€ 12	€ 484	€ 2030^{**}	€ 64
	Fertility[a]							
1st trimester	-€ 1.7	€ 156	-€ 61	€ 1755	€ 8	€ 425	€ 3607	€ 10
2nd trimester	-€ 4.0	€ 167	-€ 68	€ 2345	-€ 18	€ 735	€ 1707	€ 101
3rd trimester	€ 1.2	€ 157	€ 256	€ 2520	€ 12	€ 571	€ 2296	€ 156
	Full selection[a]							
1st trimester	€ 4.6	€ 160	€ 267	€ 1755	€ 27	€ 425	€ 5854^{+}	€ 10
2nd trimester	-€ 3.2	€ 169	-€ 86	€ 2345	-€ 122^{+}	€ 735	-€ 1172	€ 101
3rd trimester	€ 3.3	€ 157	€ 131	€ 2520	€ 2	€ 573	€ 3769^{+}	€ 156
	expenditures conditional on positive expenditures							
	all[a]							
1st trimester			€ 42	€ 2900	€ 14	€ 637	€ 527	€ 2553
2nd trimester			€ 74	€ 3073	-€ 64	€ 804	-€ 135	€ 5375
3rd trimester			€ 573^{**}	€ 2474	€ 16	€ 559	€ 114	€ 7186
	Control cities[a]							
1st trimester			€ 299	€ 3011	€ 99	€ 876	€ 1818	€ 1240
2nd trimester			€ 372	€ 2608	-€ 16	€ 658	-€ 963	€ 1783
3rd trimester			-€ 278	€ 2625	€ 62	€ 576	€ 560^{**}	€ 4339
	Fertility[a]							
1st trimester			€ 248	€ 3057	€ 15	€ 613	€ 2125	€ 1280
2nd trimester			-€ 50	€ 3448	-€ 49	€ 688	€ 935	€ 3291
3rd trimester			€ 699^{+}	€ 2532	€ 50	€ 583	€ 1104	€ 4049
	Full selection[a]							
1st trimester			€ 760	€ 2333	€ 256^{+}	€ 520	€ 1672	€ 270
2nd trimester			-€ 309	€ 2930	-€ 271	€ 816	-€ 1723	€ 1941
3rd trimester			-€ 70	€ 3178	€ 36	€ 682	€ 1373	€ 5448

[a] *all*: all controls, using whole period 1944-1947; *Control cities*: only control cities, using whole period; *Fertility*: all control born May 1944- July 1945; *Full selection*: only control cities born May 1944- July 1945

[b] DID: estimated DID; control mean: mean health expenditures 2009-2013 for those born in the control region for the given gestation period.

Included controls: Province of birth dummies, number of older brothers, religion dummies, father's occupation (6 cat.), trend and trend squared. $^{+}p < 0.05$, $^{**}p < 0.01$.

Table 8: Impact of famine exposure on health expenditures (prevalence and amount), accounting for selective survival

	IPW[a]			Copula[a]		
	(1)[b]	(2)[b]	(3)[b]	(1)[b]	(2)[b]	(3)[b]
			General practitioner			
1st trimester		€4.5			€ 8.2	
2nd trimester		-€3.0			-€10.6	
3rd trimester		€3.4			€ 5.9	
			Hospital			
1st trimester	3.21%	€267	€757	3.23%	€272	€331
2nd trimester	−1.03%	-€86	-€310	−1.03%	-€89	-€114
3rd trimester	−1.28%	€133	-€71	−1.26%	€133	€79
		Medications				
1st trimester	4.24%	€ 27	€255$^+$	4.25%	€ 28	€ 56
2nd trimester	−0.80%	-€112$^+$	-€271	−0.80%	-€114$^+$	-€116$^+$
3rd trimester	0.46%	€ 2	€ 36	0.46%	€ 2	€ 6
		Mental health				
1st trimester	14.89%	€5849$^+$	€1676	14.99%	€5894$^+$	€3602$^+$
2nd trimester	−3.54%	-€1159	-€1714	−3.54%	-€1179	-€1220
3rd trimester	−1.24%	€3765	€1372	−1.22%	€3791	€2431

[a] *IPW*: Inverse probability weighting correction for survival till 2009; *Copula*: Joint, copula, distribution for survival till 2009

[b] (1) probability of positive costs (2) total costs; (3) costs conditional on positive costs Included controls: Province of birth dummies, number of older brothers, religion dummies, father's occupation (6 cat.), trend and trend squared. $^+p < 0.05,^{**}\ p < 0.01$.

5 Conclusion

In this paper, we investigate the impact on exposure to the Dutch famine on both labor and health outcomes later in life. We use military recruits data of men born around the famine (1944-1945) linked to administrative data (1999-2013) on labor market status, income, prescribed medications and insured health expenditures. The military recruits data has been used before but not with linkage to socio-economic outcomes later in life. In this study, we use these newly linked data to estimate advanced econometric models for the impact of famine exposure on these outcomes.

Scholte et al. (2015) is the only other study that investigated the impact of the Dutch famine on socio-economic outcomes later in life. They looked at labor supply, income and hospitalization. In contrast to Scholte et al. (2015) we view both labor market status and the health outcomes as a dynamic process instead of a static outcome, a snapshot at 1999. We use the whole labor market process from 1999 till retirement We do not consider the timing of employment and unemployment transitions, because these labor market transitions are known to be influenced by the whole labor market history (since entry to the labor market, after finishing education) and, unfortunately, we only start observing the labor market status in 1999, when the men born around the famine are around 55 years old. The employment status in 1999, that Scholte et al. (2015) use as outcome variable, is a snapshot of an evolving process of labour market transitions and therefore ignores important aspects of this process. The results may be different if they had used another year to measure the employment status. They mention that later years are confounded by early retirement. That is one of the reasons why we focus on the retirement process. We also think that retirement and disability are more related to health than employment and therefore more likely to be affected by the famine (if the famine has an health impact).

Another difference with their approach is that we account for selective fertility due to the famine. The fertility in the Netherlands dropped dramatically in the months after the famine. It is very likely that women with less access to food were less likely to become pregnant, which implies that the men who were born have a more healthy/wealthy background. Third, we use a different set of control cities than Scholte et al. (2015). They only used Breda, Eindhoven Enschede, Groningen, Heerlen, Hengelo, Leeuwarden, Maastricht, Tilburg and Zwolle as control cities, while we have a more extended set of control cities in total. For the labor market outcomes (disability/retirement hazard, and income) we only find a small influence of the choice of the control group when estimating the impact of the famine on income later in life. Exposure to the famine in the first trimester of gestation only has a statistically significant impact on income when using all controls without fertility selection. For the health outcomes (medication use and health expenditures) we find a slightly larger influence of the choice of the control group. Still, only for a few cases we find a statistically significant impact of famine exposure.

Fourth, we account for selective survival, the possibility that a selective sample of the original recruits survived till the first observation moment of labor (1999), income (2003), medication use (2006) or health expenditure (2009). We compare the results for accounting for selective survival using an inverse propensity weight method and a Copula approach. The first method imposes no selection on unobservables, while the second imposes a parametric link function between the marginal distribution of survival and the marginal distribution of the outcome. Although using a Copula approach to account for selective attrition changes has a larger impact on the estimated famine exposure effects are in most cases still statistically insignificant, with the exception of mental health medications.

Scholte et al. (2015) find that the probability of employment at age 55 is significantly lower if the individual was exposed to the famine in the first trimester of gestation and that hospitalization rates are higher for individuals exposed to the famine in the second or third trimester of gestation. We find that famine exposure in the first trimester of gestation accelerates the timing of disability. Just as Scholte et al. (2015) we do not find any impact of exposure to the famine on income later in life.

We are the first to investigate the impact of the Dutch famine on medication use and health expenditures, both health related outcomes. We find that famine exposure in the first trimester of gestation increases the expenditures for mental health. Exposure in the second trimester decreases expenditure for medications. Exposure in the third trimester increases medication use for mental diseases (psycholeptics medication).

The reason we only find limited significant results might be driven by the limited number of individuals in the control cities (especially for mental medication use and expenditures). Ekamper et al. (2015) have investigated the impact of the famine on cause-specific mortality and their conclusion of the absence of an influence of famine exposure on death due to cardiovascular diseases or cancers is in line with our results of the absence of an effect on most medications due to the famine. The increased death due to external causes (including suicide) due to the famine Ekamper et al. (2015) have found is in line with our finding of an increased probability of psycholeptics prescription. Another limitation is that we do not have information for women as they were never called for conscript military service in the Netherlands. It is, therefore, not possible to compare sex-specific outcomes using our data.

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Appendix A Likelihood for Copula approach

In a copula approach the joint distribution of two (or more) random variables is induced by the marginal distributions and a function that links them together, the copula. (Smith, 2003) has shown that it provides a approach to sample selection models. Trivedi and Zimmer (2007), Fan and Patton (2014) provide more details and applications of copula models in econometrics. With it relation with frailty (unobserved heterogeneity) modelling the use of copula models for survival analysis has a long history, see (Georges et al., 2001) for a detailed description. In this appendix we give the likelihood construction for the labor transition hazard rate model with a Clayton copula and (left truncation).

Let denote T_e denote the time till a labor market transition (either disability or retirement) and T_d time till death. The joint distribution of these two survival times based on a Clayton copula is:

$$S(t_e, t_d) = \Big[S_e^{-\theta}(t_e) + S_d^{-\theta}(t_d) - 1\Big]^{-1/\theta} \tag{A.1}$$

$$= \Big[\exp\big(\Lambda_e(t_e)/\theta\big) + \exp\big(\Lambda_d(t_d)/\theta\big) - 1\Big]^{-1/\theta} \tag{A.2}$$

with $\theta \in (0, 1)$ the copula parameter which governs the dependence between T_e and T_d. $\Lambda_j(t_j)$, $j \in \{e, d\}$ is the cumulative hazard function of the relevant survival time. We assume a Gompertz distribution for the mortality survival, i.e. $\Lambda_d(t_d) = \exp(\beta_d x)\big(e^{\gamma_d t_d} - 1\big)/\gamma_d$. The distribution of the labor market transition times are either Gompertz (retirement) or piecewise constant (disability), see Section 3.1.

For the construction of the likelihood function we need to account for left-truncation and/or right-censoring. We provide the individual likelihood contribution for the different situation:

- Mortality before 1-1-1999, i.e. only death observed

$$L_i = \lambda_d(t_d) S_d(t_d) = e^{\beta_d x + \gamma t_d} \exp\big(-\Lambda_d(t_d)\big) \tag{A.3}$$

- Mortality after 1-1-1999 and both labor market and mortality censored, i.e. conditional on survival till 1-1-1999

$$L_i = \exp\big(\Lambda_d(t_{99})\big) S(t_e, t_d) \tag{A.4}$$

  with t_{99} is the age at 1-1-1999.

- Mortality after 1-1-1999 and labor market censored

$$\begin{aligned} L_i &= \exp\big(\Lambda_d(t_{99})\big)\partial S(t_e, t_d)/\partial t_d \\ &= \exp\big(\beta_d x + \gamma t_d + \Lambda_d(t_d)/\theta + \Lambda_d(t_{99})\big)\Big[\exp\big(\Lambda_e(t_e)/\theta\big) + \exp\big(\Lambda_d(t_d)/\theta\big) - 1\Big]^{-1/\theta-1} \end{aligned} \tag{A.5}$$

- Labor market transition after 1-1-1999 and mortality censored

$$\begin{aligned} L_i &= \exp\big(\Lambda_d(t_{99})\big)\partial S(t_e, t_d)/\partial t_e \\ &= \lambda_e(t_e)\exp\big(\Lambda_e(t_e)/\theta + \Lambda_d(t_{99})\big)\Big[\exp\big(\Lambda_e(t_e)/\theta\big) + \exp\big(\Lambda_d(t_d)/\theta\big) - 1\Big]^{-1/\theta-1} \end{aligned} \tag{A.6}$$

- Labor market transition and mortality after 1-1-1999 and mortality after labor market transition

$$\begin{aligned} L_i &= \partial^2 S(t_e, t_d)/\partial t_e \partial t_d \\ &= \frac{\frac{\theta+1}{\theta}}{\exp\big(\Lambda_e(t_e)/\theta\big) + \exp\big(\Lambda_d(t_d)/\theta\big) - 1}\left[\frac{\exp\big(\Lambda_e(t_e)/\theta\big) + \exp\big(\Lambda_d(t_d)/\theta\big) - 1}{\exp\big(\Lambda_e(t_e)/\theta\big) + \exp\big(\Lambda_d(t_{de})/\theta\big) - 1}\right]^{-1/\theta-1} \end{aligned} \tag{A.7}$$

  with t_{de} is the age when the labor market transition occurs.

- Labor market transition before 1-1-1999 and mortality censored

$$L_i = \exp\big(\Lambda_d(t_{99})\big)\Big[\exp\big(-\Lambda_d(t_d)\big) - S(t_e, t_d)\Big] \tag{A.8}$$

- Labor market transition before 1-1-1999 and mortality after

$$\begin{aligned} L_i &= \exp\big(\Lambda_d(t_{99})\partial\Big[\exp\big(-\Lambda_d(t_d)\big) - S(t_e, t_d)\Big]/\partial t_d \\ &= \exp\big(\beta_d x + \gamma t_d + \Lambda_d(t_{99})\big) \times \qquad \text{(A.9)} \\ &\Bigg[\exp\big(-\Lambda_d(t_d)\big) - \exp\big(\Lambda_d(t_d)/\theta\big)\Big[\exp\big(\Lambda_e(t_e)/\theta\big) + \exp\big(\Lambda_d(t_d)/\theta\big) - 1\Big]^{-1/\theta-1}\Bigg] \qquad \text{(A.10)} \end{aligned}$$

Combining these likelihood contributions give the full likelihood. We use maximum likelihood estimation to estimate he parameters.

Appendix B Additional tables and figures

Figure B.1: Disability development by famine region, selection and gestation period

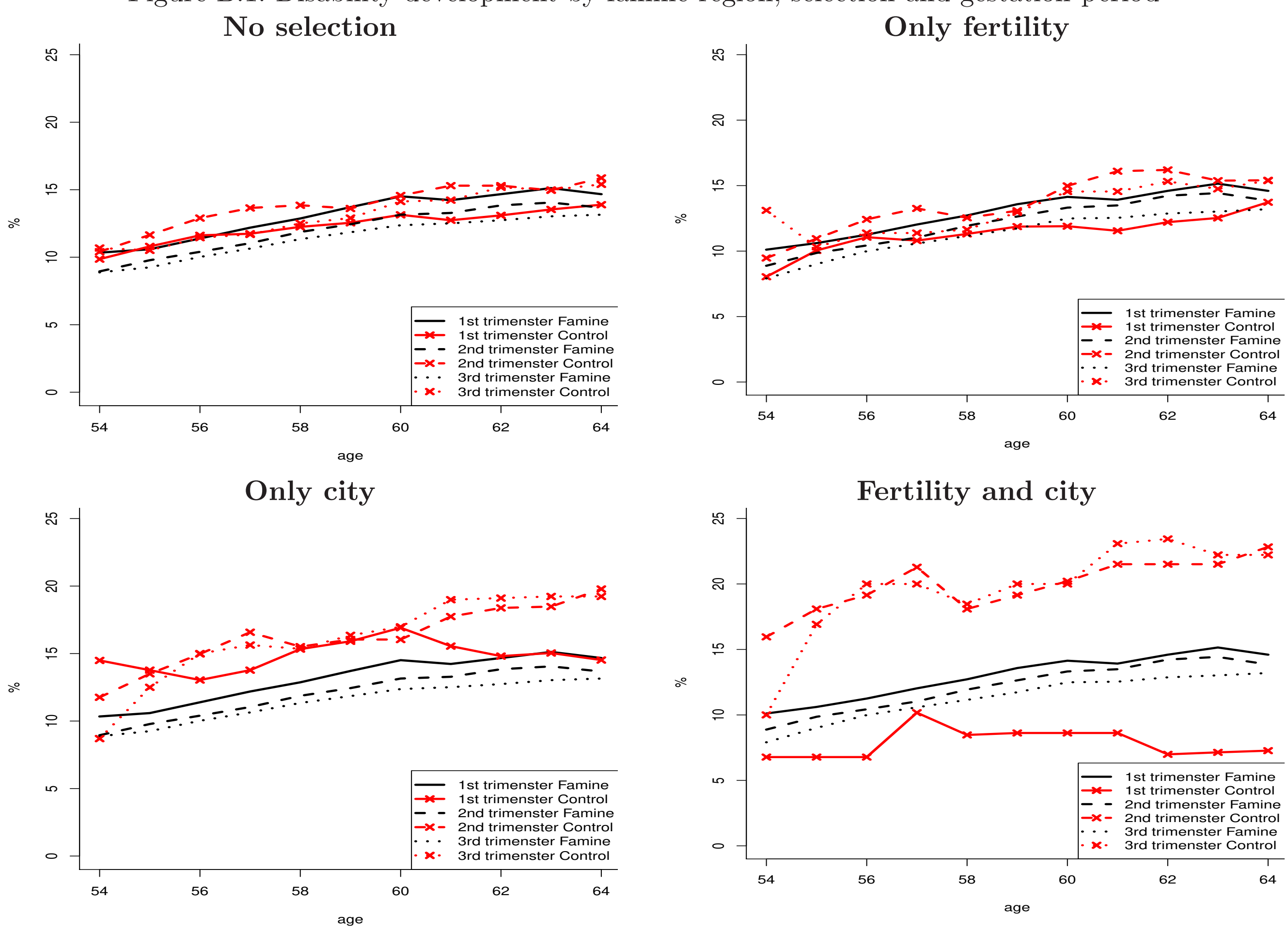


Figure B.2: Difference in disability development between famine and control cities by selection and gestation period

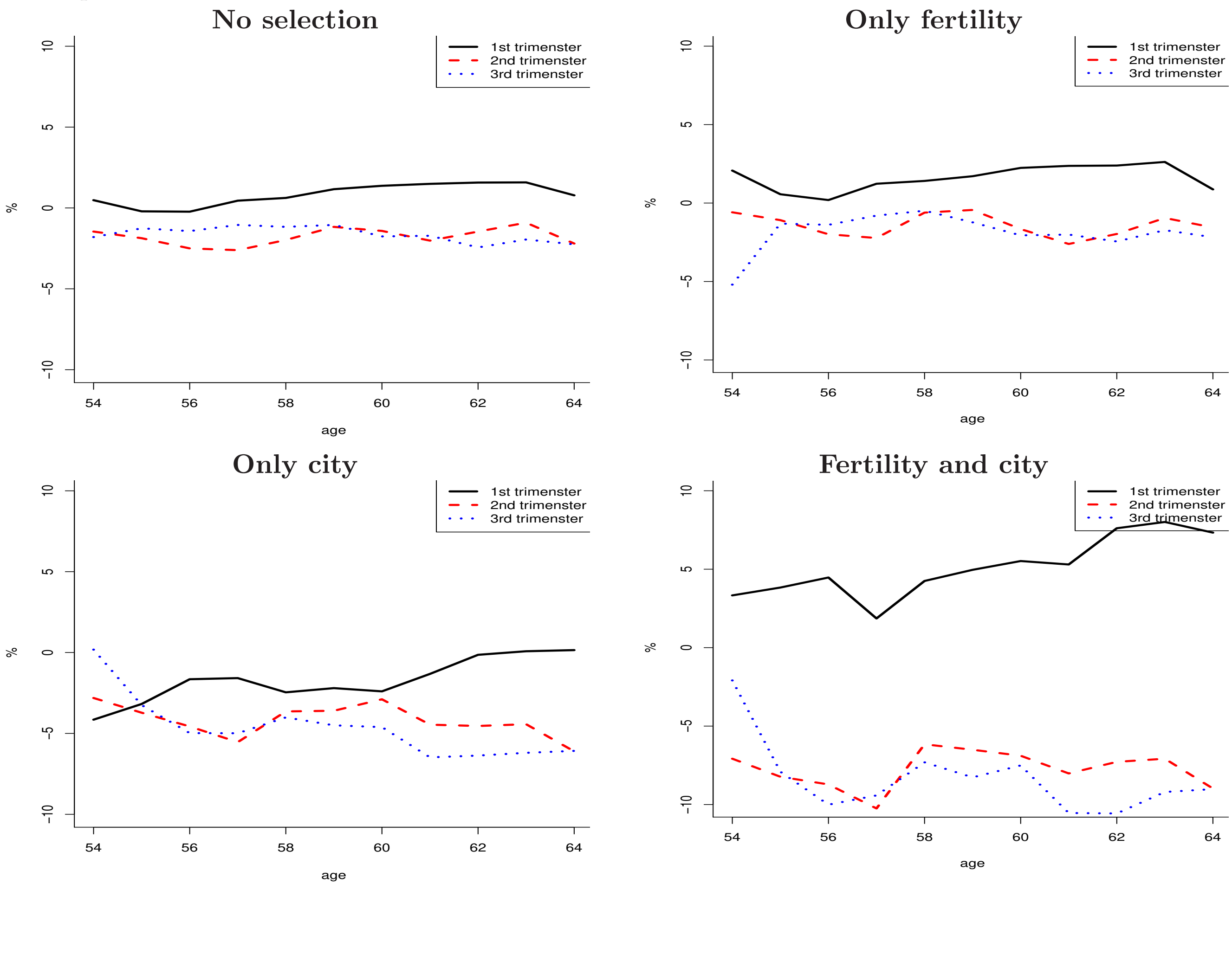


Table B.1: Labor market status in 1999 by famine exposure period: famine cities vs control, by selection

	working	disabled	unemployed	retired
No selection				
	Famine cities, $N = 29,043$			
1^{st} trimester	82.60%	15.03%	8.18%	5.44%
2^{nd} trimester	84.09%	14.24%	8.01%	4.80%
3^{rd} trimester	84.15%	13.81%	8.06%	5.12%
	control cities, $N = 7,271$			
1^{st} trimester	84.74%	15.26%	5.40%	4.93%
2^{nd} trimester	86.47%	16.44%	6.56%	5.72%
3^{rd} trimester	86.54%	15.82%	5.19%	5.08%
	DID[a]			
1^{st} trimester	0.15%	1.35%	0.80%	−0.47%
2^{nd} trimester	0.17%	−0.73%	−0.71%	−1.88%$^{+}$
3^{rd} trimester	−0.16%	−0.48%	0.97%	−1.05%
Only fertility selection				
	Famine cities, $N = 29,043$			
1^{st} trimester	82.60%	15.03%	8.18%	5.44%
2^{nd} trimester	84.09%	14.24%	8.01%	4.80%
3^{rd} trimester	84.15%	13.81%	8.06%	5.12%
	control cities, $N = 1,393$			
1^{st} trimester	78.99%	17.39%	6.52%	5.80%
2^{nd} trimester	82.89%	16.04%	6.42%	4.81%
3^{rd} trimester	81.88%	17.50%	7.50%	5.63%
	DID[a]			
1^{st} trimester	2.51%	−0.85%	0.00%	−1.75%
2^{nd} trimester	−0.11%	−0.18%	−0.13%	−1.37%
3^{rd} trimester	1.27%	−2.39%	−1.34%	−2.04%
Only city selection				
	Famine cities, $N = 12,873$			
1^{st} trimester	82.50%	15.14%	8.20%	5.78%
2^{nd} trimester	83.99%	14.55%	7.94%	4.98%
3^{rd} trimester	84.09%	13.82%	7.80%	5.46%
	control cities, $N = 391$			
1^{st} trimester	85.18%	14.82%	7.29%	6.78%
2^{nd} trimester	85.05%	18.11%	9.05%	6.11%
3^{rd} trimester	84.13%	18.25%	6.08%	5.82%
	DID[a]			
1^{st} trimester	−0.89%	1.70%	−1.03%	−2.34%
2^{nd} trimester	0.69%	−2.07%	−3.02%	−2.46%
3^{rd} trimester	1.34%	−2.70%	0.20%	−1.70%

[a] Difference-in-difference estimation with included controls: Province of birth dummies, number of older brothers, religion dummies, father's occupation (6 cat.), trend and trend squared

Figure B.3: Retirement development by famine region, selection and gestation period

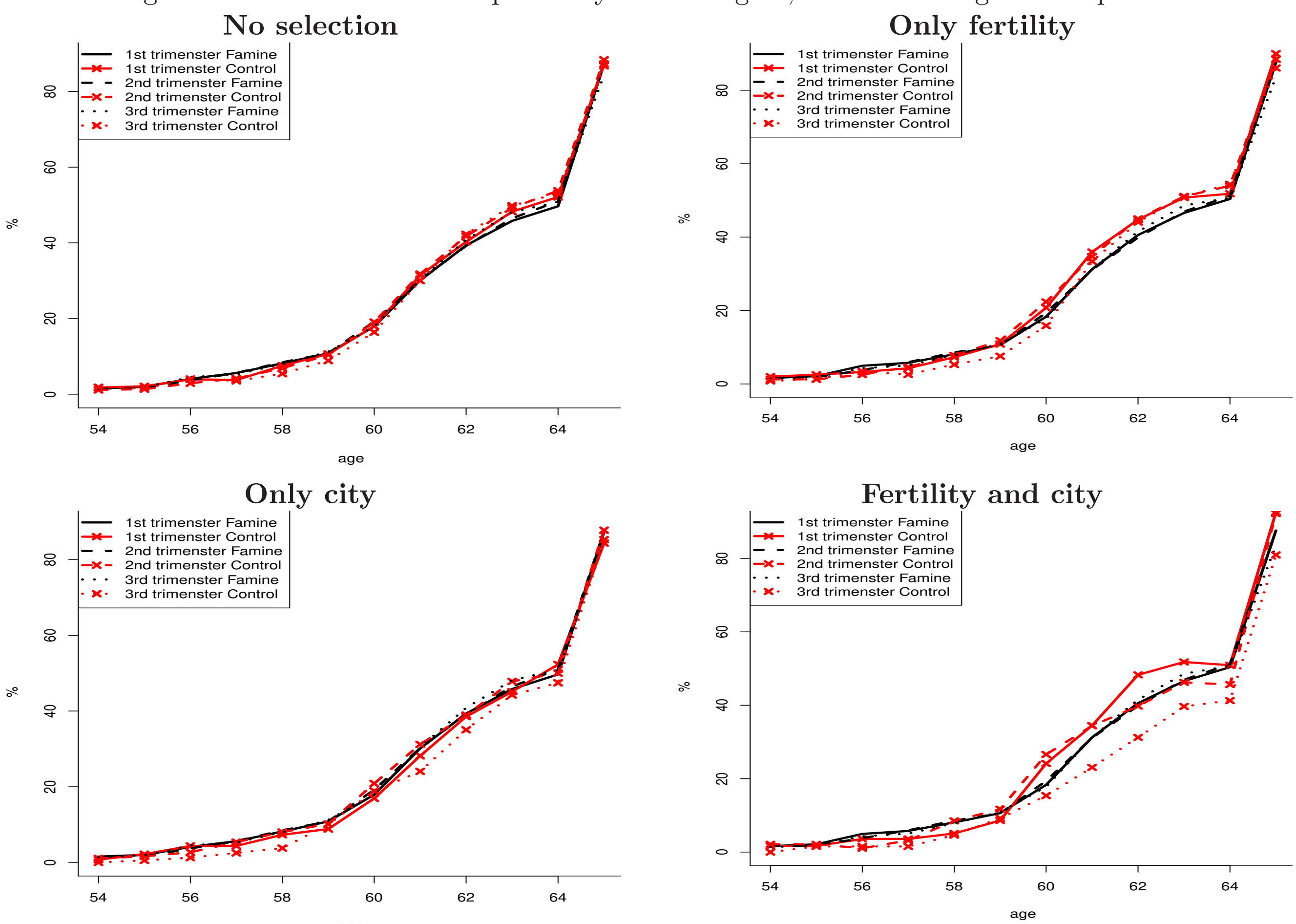


Figure B.4: Difference in retirement development between famine and control cities by selection and gestation period

Figure B.5: Development of real annual income by famine region, selection and gestation period

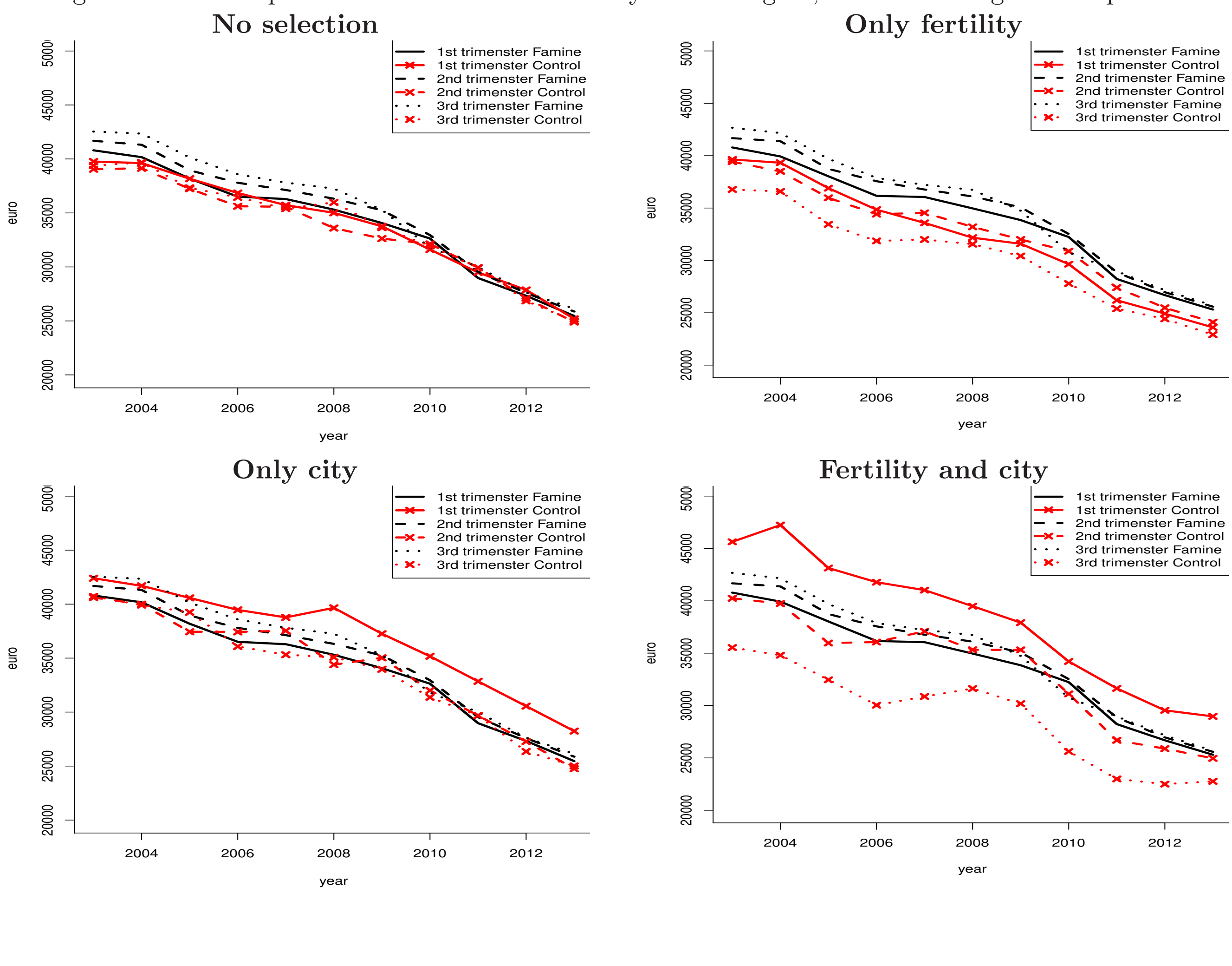


Figure B.6: Difference in real annual income between famine and control cities by selection and gestation period

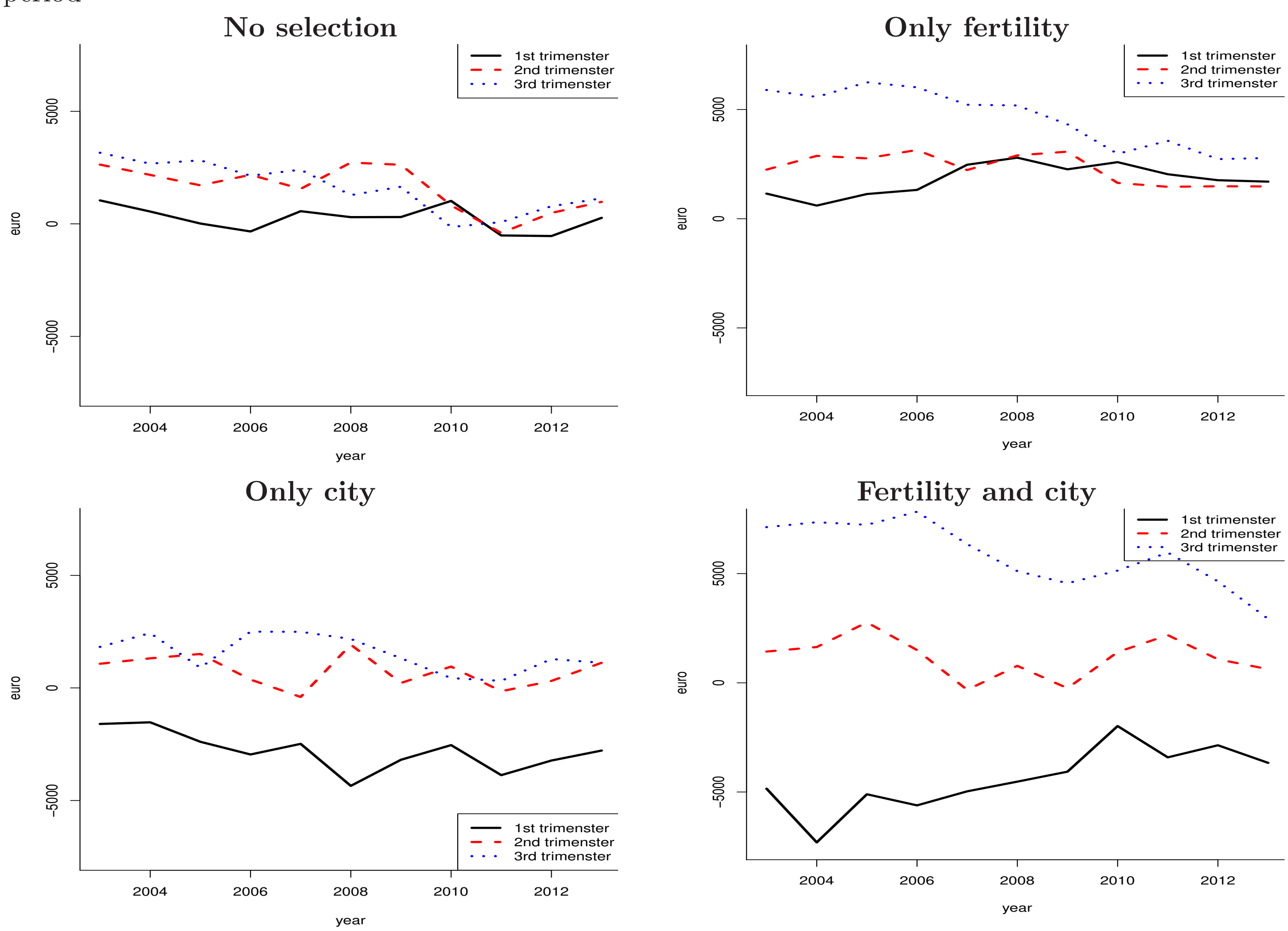


Figure B.7: Development of prevalence of prescribed mediations by famine region, selection and gestation period

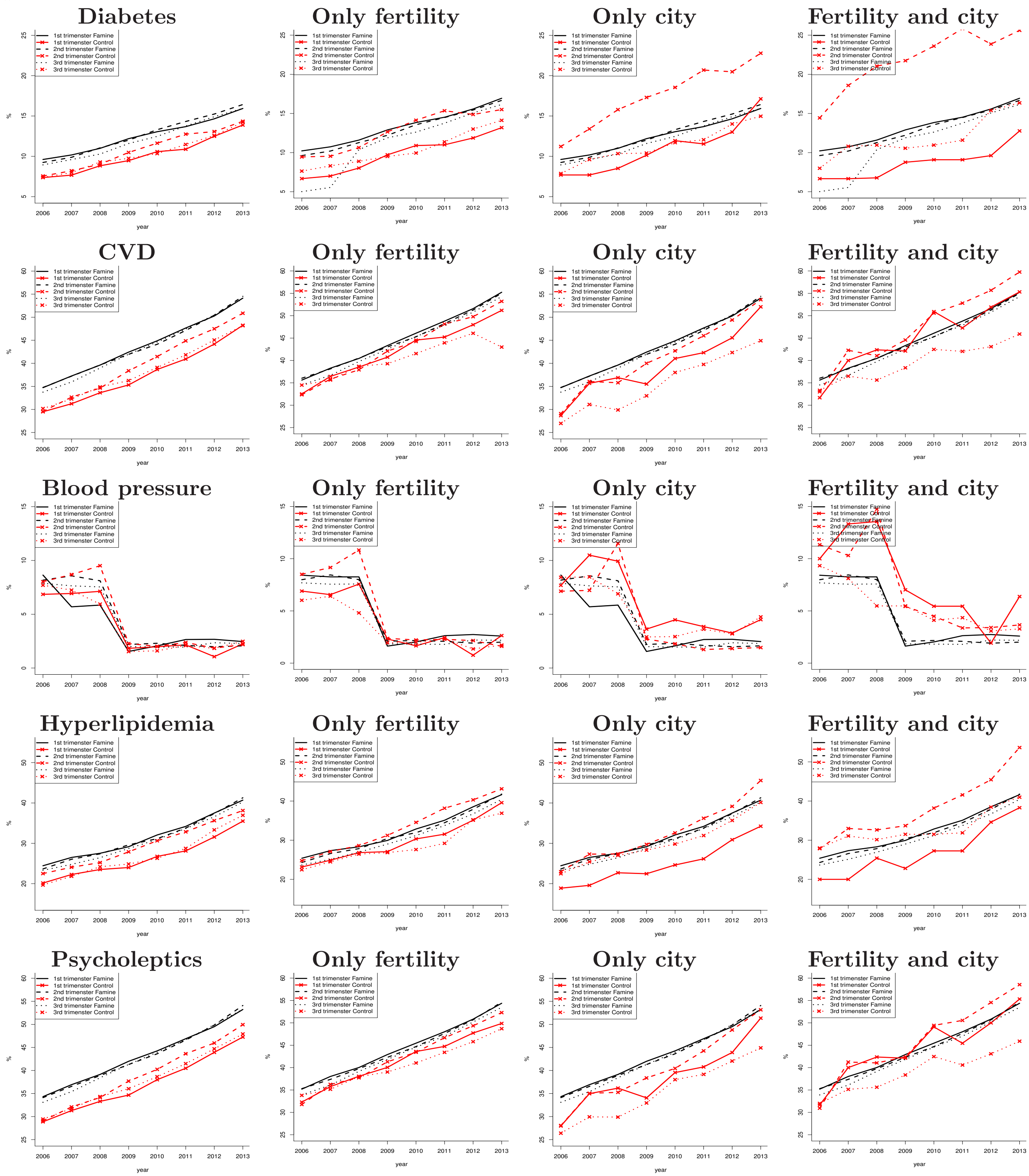


Figure B.8: Development of difference in prevalence of prescribed mediations between famine and control cities by selection and gestation period

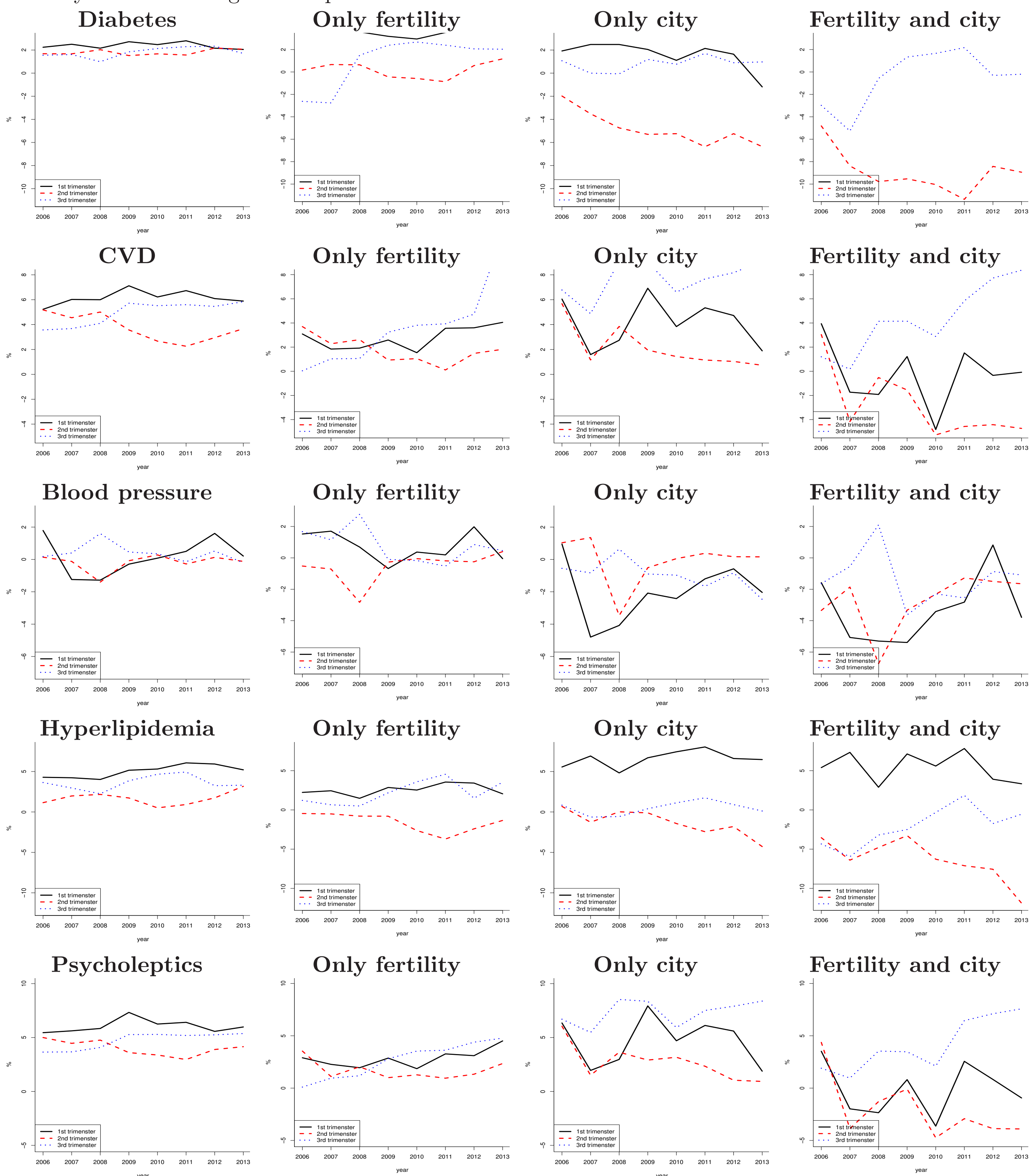


Figure B.9: Development of prevalence of positive health expenditures by famine region, selection and gestation period

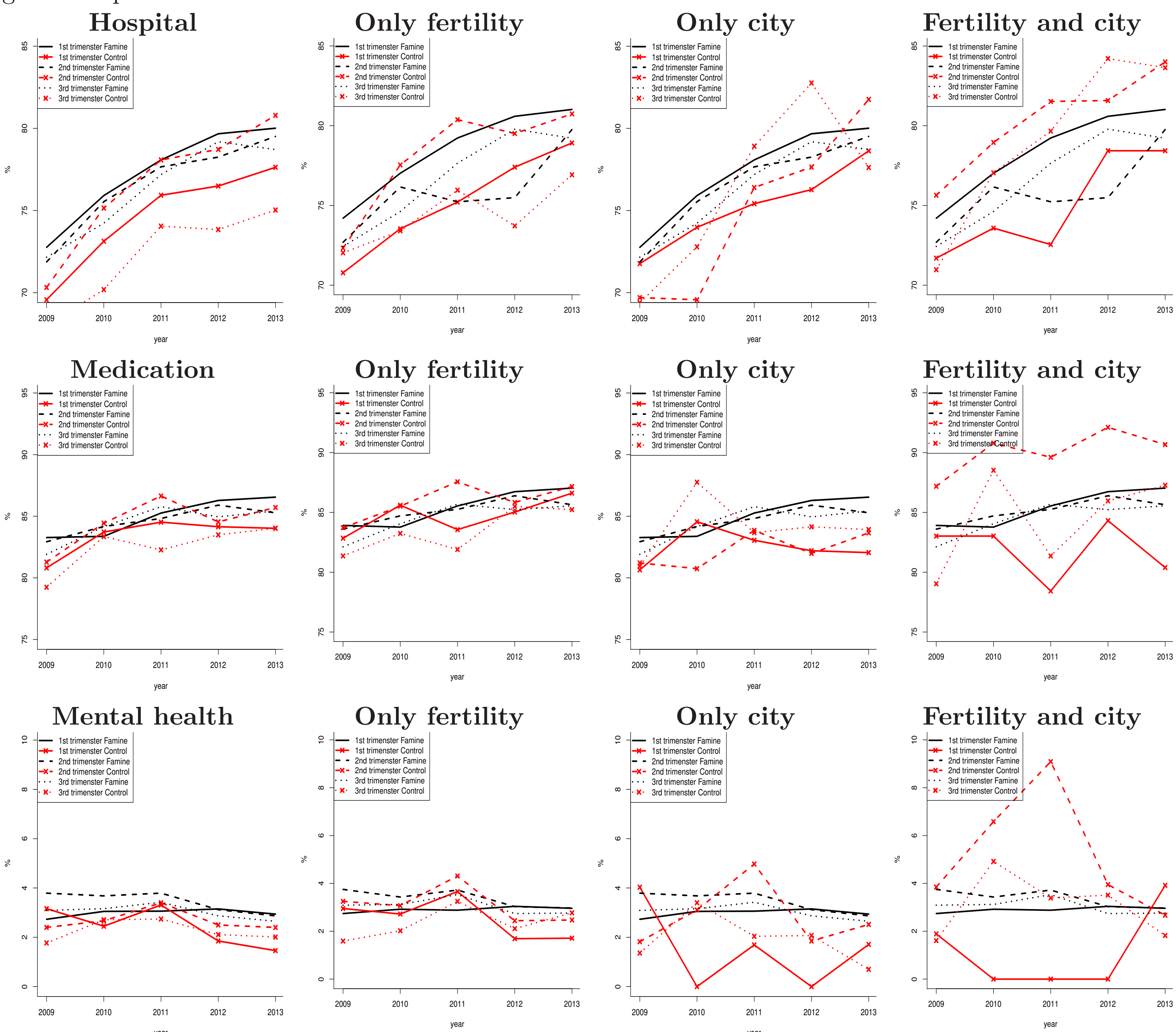


Figure B.10: Development of difference in prevalence of positive health expenditures between famine and control cities by selection and gestation period

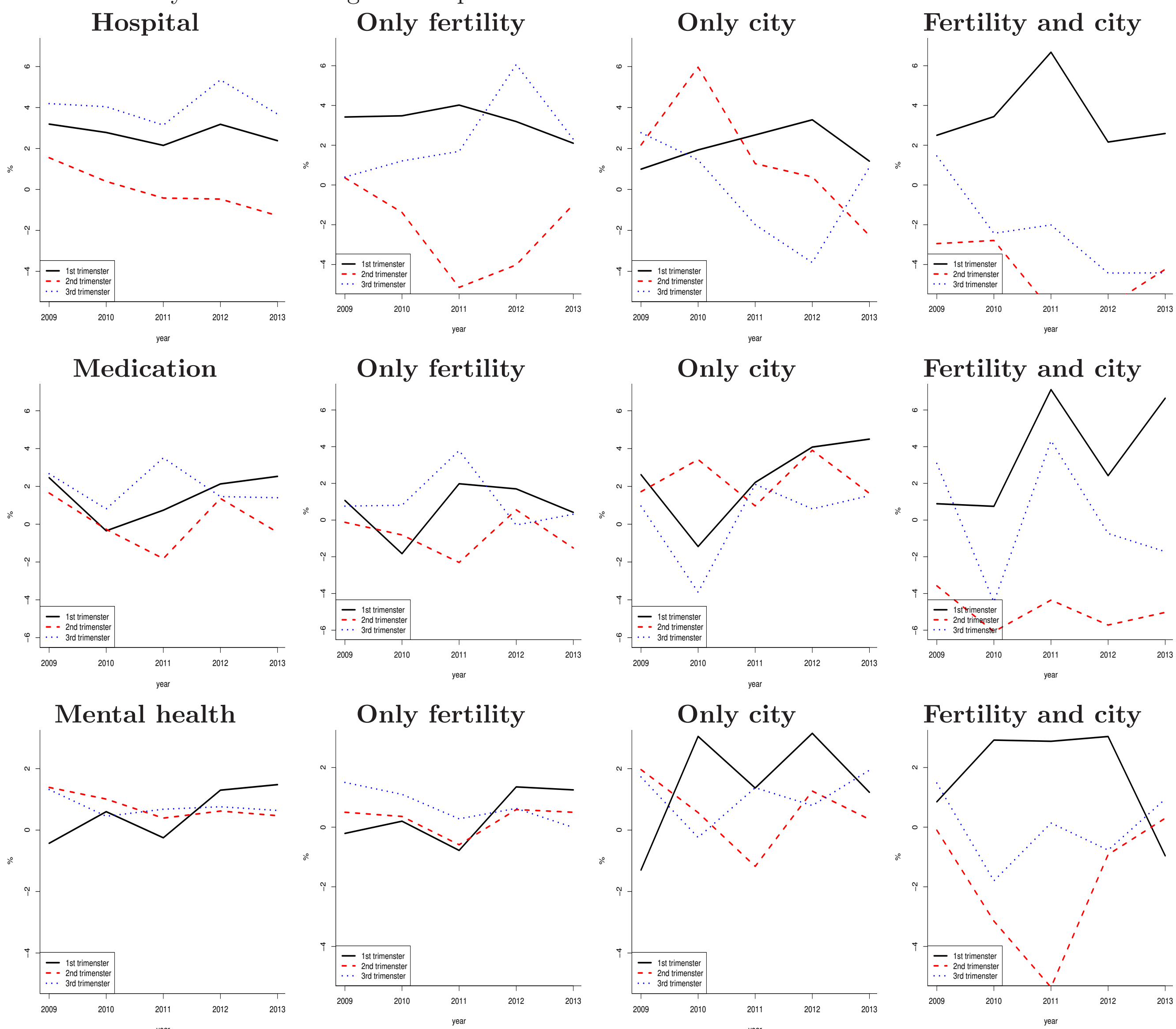


Figure B.11: Development of health expenditures by famine region, selection and gestation period

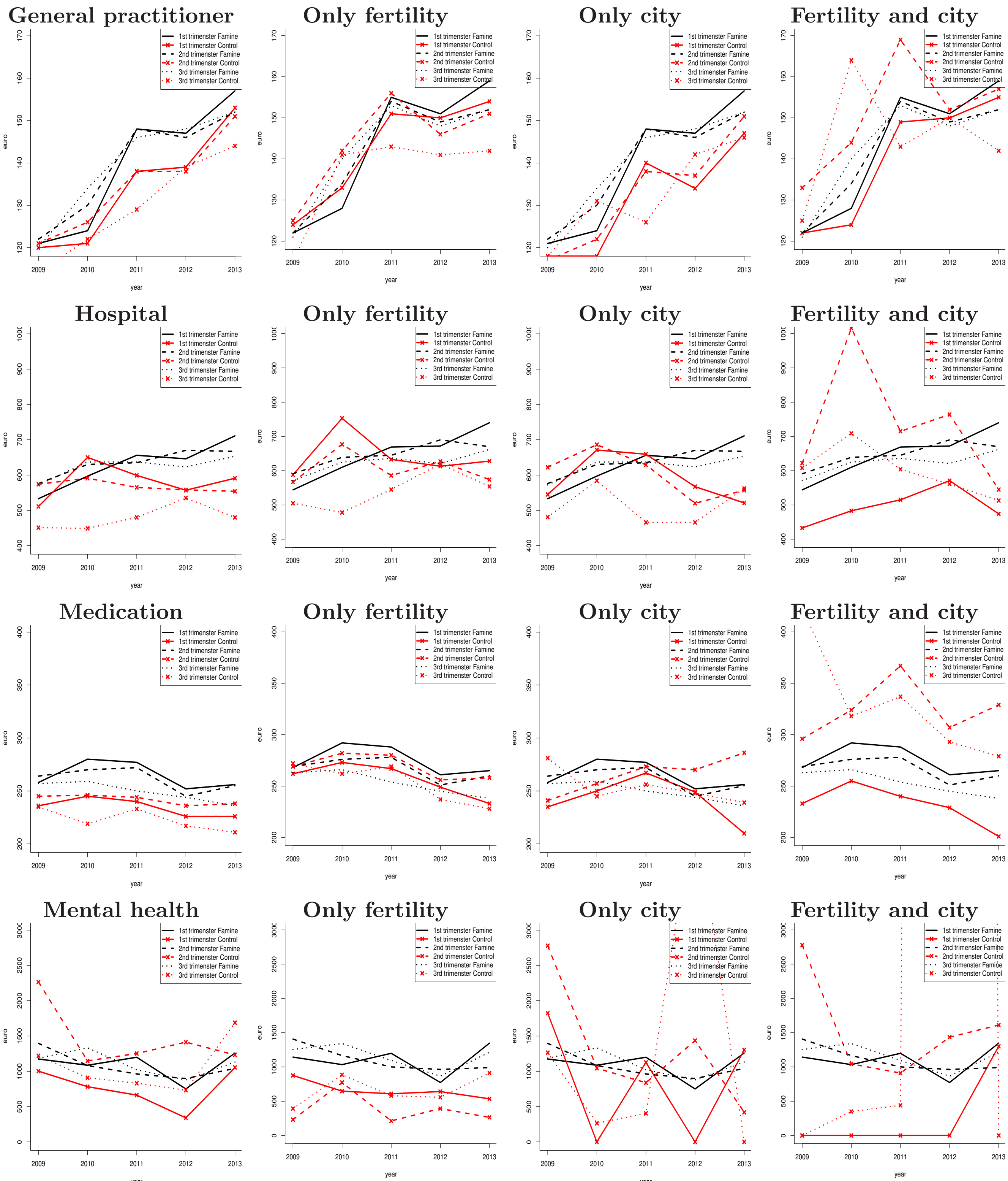


Figure B.12: Development of difference in health expenditures between famine and control cities by selection and gestation period

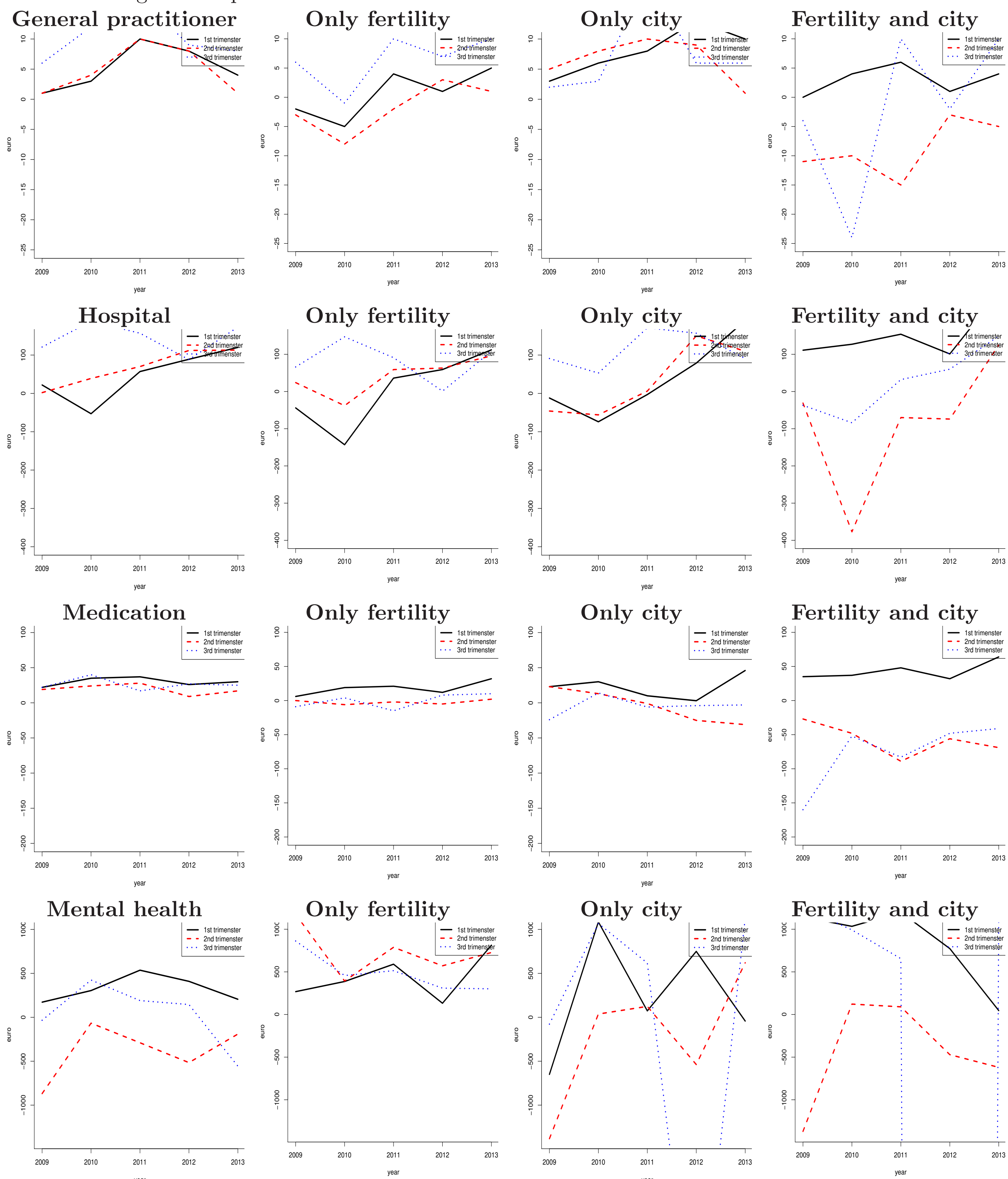
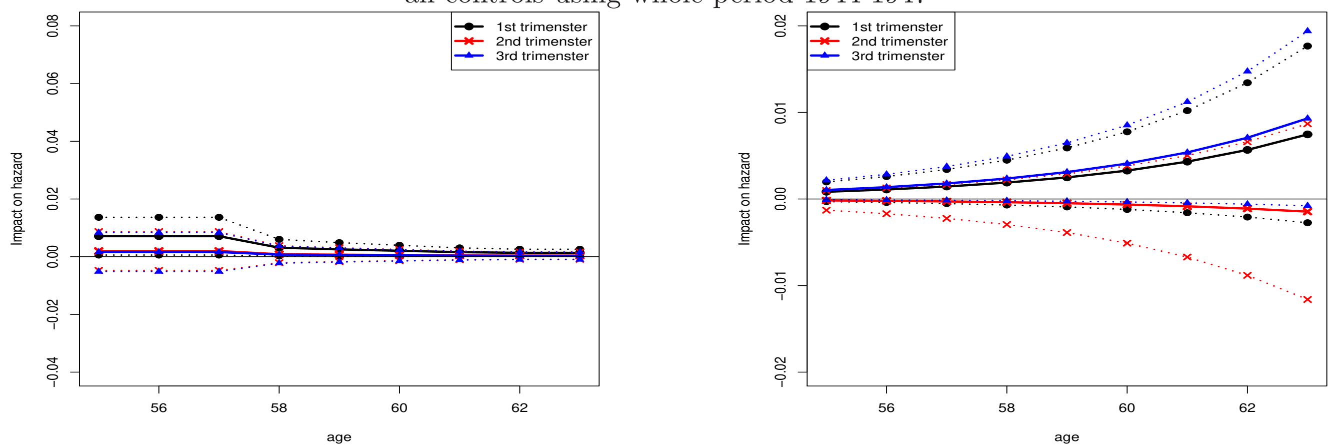
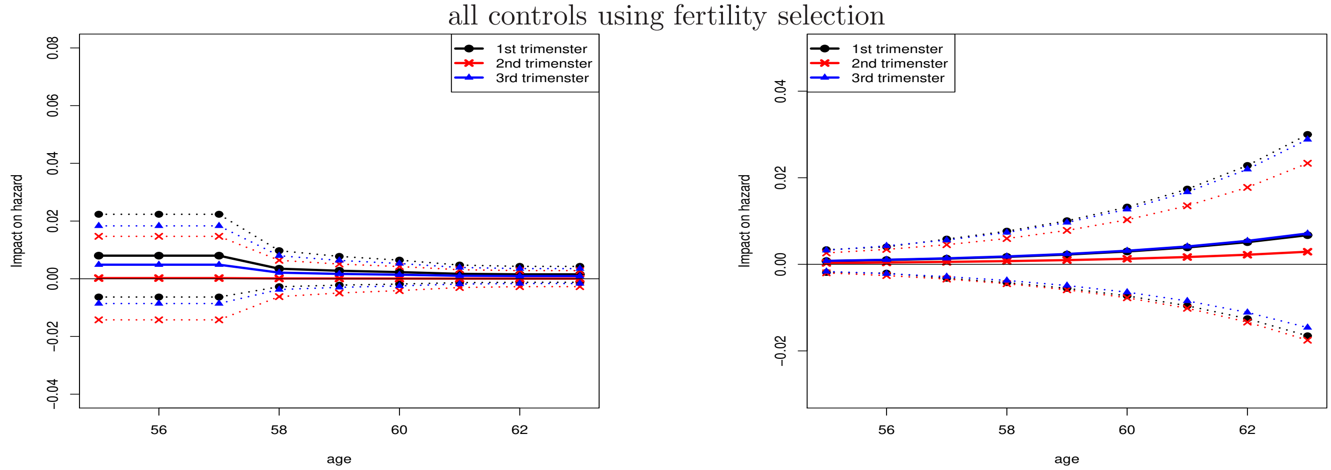


Figure B.13: Impact of famine on the disability and retirement hazard, by selection

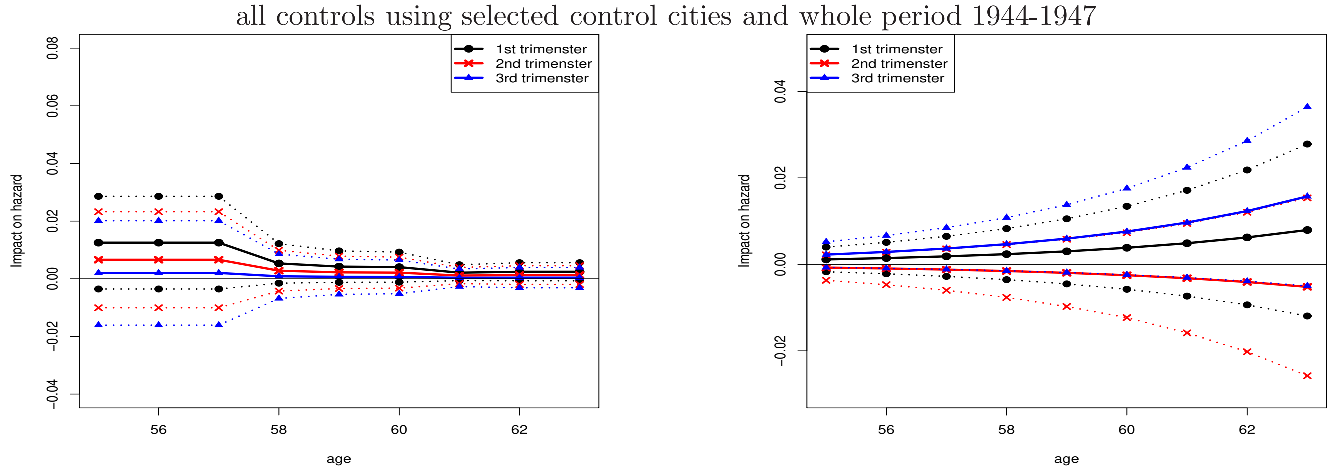
all controls using whole period 1944-1947



all controls using fertility selection



all controls using selected control cities and whole period 1944-1947



Disability **Retirement**

Notes: Impact in change of annual hazard rate. The dotted lines are the 95% confidence bounds.