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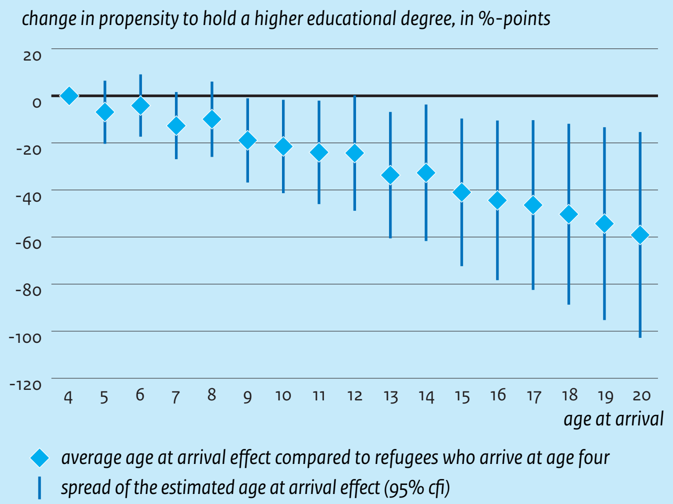
Arriving at an old age reduces educational attainment



CPB Discussion Paper

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The impact of age at arrival on education and mental health *

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Abstract
Given the importance of education and mental health for labor market performance, we study how these outcomes are affected by the age at which refugees arrive in the country. We identify the causal impact of age at arrival by comparing siblings who share the same family background characteristics, but arrive at different ages. We find significant and meaningful impacts of age at arrival on educational attainment, but not on mental health. Arriving one year earlier increases the probability to obtain a higher educational degree by 3.6 percentage points. We find this impact to be stronger for girls than for boys. We do not find evidence suggesting that the impact of age at arrival becomes more pronounced after a specific age. Our findings carry important policy implications for the allocation of scarce resources available for integration of refugees as we show that refugee children who arrive at an older age will have substantially reduced educational outcomes compared to those who arrive at a younger age. This also implies that child refugees arriving via family reunification would benefit substantially from reductions in asylum application processing time, even if realized reductions are small.

JEL: I10; I21; J61; C21

Keywords: refugees; age at arrival; Immigration; sibling fixed effects

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1. Introduction

According to the UN the number of refugees has never been higher than today's 25.4 million, of whom fifty percent are children under the age of 18 (UNHCR, 2018). Many destination countries struggle with the new influx of refugees, in particular with the question how to integrate them into their societies. Worries about their labor market integration are widespread, and based upon the fact that refugees and their children perform worse on many key indicators measuring labour market performance. Refugees are more likely to work in unskilled sectors like agriculture, construction, cleaning services and retail trade. They are also less likely to be employed, even if they have been in the country for ten to fifteen years or longer, see Connor (2010), Desiderio (2016), Bakker et al. (2017), Dustman et al. (2017), Bevelander (2016) and Fasani et al. (2017).[1]

The economic literature provides at least two explanations for these findings. First, refugees and their children leave their home countries often involuntarily, and sometimes even illegally, to escape violence or persecution. The forced nature of their migration decision decreases their mental health (Lustig et al., 2004; Fazel et al., 2012), which hampers their labor market performance (Giuntella et al. 2018; Ruiz and Vargas-Silva, 2018). Second, uncertainty about their allowed length of stay reduces the incentive to invest in human and social capital (Dustmann and Glitz, 2011). Less human capital in general reduces labor market performance as well (see overviews in Psacharopoulos and Patrinos, 2004 and Heckman et al., 2006). Hence, educational attainment and mental health could be important explanations why refugees have a weak labor market performance.[2]

Recent studies by Evans and Fitzgerald (2017) and Maliepaard et al. (2017) suggest that age at arrival might be an important driver of the educational attainment of refugees: refugees who enter the destination country at a young age have similar educational outcomes as natives, while those who arrive at a later age have lower attainment rates. In addition, a literature review by Fazel et al. (2012) lists empirical evidence for a negative relationship between refugee age at arrival and mental

[1] Yet the underperformance of refugees is not a deterministic law: a study by Cortes (2004) for the US suggests that refugees outperform other migrants in the long run. Refugees tend to find work faster in the US and Canada than in Europe (Moussa, 2018). These differences across continents could well be due to host country differentials in refugee services and programs as suggested by Bevelander and Pendakur (2014), Dustman et al. (2017) and Fasani et al. (2017).

[2] Of course, these are not the only drivers of refugee labor market outcomes. Working bans prohibit refugees from working shortly upon arrival (Fasani et al., 2017), which could lead to 'scarring effects' that could be long-lasting. The uncertainty of the asylum process demotivates refugees to integrate economically into the host society (Hainmuller et al., 2016). And in many countries, refugees who receive a residence permit are subject to a random dispersion policy, which reduces the quality of the match between region and refugee (Bansak et al., 2018). Finally, labor market discrimination against refugees could explain why refugees have a weaker labor market performance compared to natives, but it is less likely to explain the weaker labor market performance of refugees compared to regular migrants (Kaas en Manger, 2012; Blommaert et al., 2014; Bertrand and Mullainathan 2014.)

health. However, these results are mere correlational in nature, and it's difficult to give them a causal interpretation.

In this study we try to fill this gap by providing the first causal estimates of the effect of age at arrival on educational performance and mental health for refugees. Our empirical strategy relies on the inclusion of family fixed effects to control for unobserved heterogeneities at the family-level.[3] This empirical strategy has been successfully applied to the children of migrants to explain educational performance (Bohlmark, 2008; Lemmerman and Riphahn, 2018), health and mental health (Van den Berg et al., 2014) as well as social integration and a broad set of economic outcomes later in life (Åslund et al., 2015; Hermansen, 2017, Gielen and Webbink, 2018).[4] These previous studies on migrants suggest that the age at which refugees arrive in the destination country negatively effects educational attainment and mental health. Driving mechanisms seem to be the better language proficiency by migrants who arrive at a young age and the fact that young arrivals are exposed for a longer time period to the (better) living conditions in the destination country and to the culture of the destination country.[5]

Yet it is unclear whether we can extrapolate these results for migrant to refugees. There are several reasons why results for refugees could be stronger. Refugees migrate involuntarily to avoid violence, civil war or other types of conflict, which generates stress and negatively affects physical and mental health (Lustig et al., 2004; Fazel et al., 2012). Giuntella et al. (2018) find that refugees with a long lasting health condition report this restricts them in the hours they work or the type of job they want to do. Ruiz and Vargas-Silva (2018) report that differences in physical and mental health status explain part of the refugee gap in labor market performance. Note that the forced nature of the migration decision could affect children within families differently. For instance, forced migration

[3] These family fixed effects effectively control for unobserved heterogeneities like timing of migration, cultural and linguistic background of the family, family attitude towards the host society, or family-level characteristics such as ability of the parents, preferences or wealth. As the Dutch asylum procedures prescribes that families remain united during the asylum procedure, these family fixed effects also control for heterogeneities in the asylum procedure that could affect performance later in life such as the uncertainty and length of the asylum procedure (Hainmuller et al., 2016; Dustman et al, 2017), the outplacement region (Bansak et al., 2018) or quality of asylum centers (Gould et al., 2014).
[4] Recently Chetty and Hensen (2018) use siblings in moving households have been used to identify neighborhood effects in the United States.
[5] The age at which migrants and refugees arrive might affect performance in the host society later in life, because younger arrivals can acquire more human capital and social capital that is specific to the destination country (Dustmann, 1993; 1999; 2000). Also, the critical age hypothesis states that mastering a foreign language becomes harder after the onset of puberty because of both biological and experiential mechanisms (Singleton, 2001; Birdsong, 2006). Young arrivals then might be more productive directly (as they are more able to communicate with co-workers and understand the tasks being asked) and indirectly as it lowers the (non-pecuniary) costs of education. See Dustmann and Glitz (2011) and Chiswick and Miller (2015) for a discussion on the role of language proficiency on labor market performance.

might generate less stress to young refugees as their cognitive capabilities are less developed at that stage.

In addition, many refugees receive a temporal residence permit and do not know how long they are allowed to stay in the destination country. This contrasts to the experience of regular migrants who often know beforehand for how long they are allowed to stay upon arrival and which criteria should be met in order to prolong their residence permit. The uncertainty about the duration in the destination country negatively affects human capital decisions, which could reduce labor market performance in turn (Dustmann and Glitz, 2001). This also holds within families: After several years part of this uncertainty is reduced, which might be more beneficial to young children in a family for whom the decision how much to invest in human capital still has to be made.

The main conclusions from our study are threefold. First, our results suggest that refugee age at arrival has a strong effect on educational performance. Arriving one year earlier increases the probability of having a higher education diploma by about 3.6 percent. Qualitatively similar effects are found for other measures of educational attainment. The effect on educational performance is stronger for girls than for boys, which suggests the difference in culture between the home and destination country affects female educational attainment more strongly (cf. Van Ours and Veenman, 2006).[6]

Second, the effects of age at arrival on educational outcomes for refugees are stronger than those found by other scholars for migrants. This could imply that this impact of age at arrival is larger for refugee children than for children of migrants arriving at the same age. However, we cannot rule out that the difference is driven by differences in destination countries. Also, we do not find evidence that the impact of age at arrival becomes more pronounced after a certain age. This is in line with Åslund et al. (2015) who also do not find evidence for a critical age when studying the impact of age at arrival on social integration, but it contradicts results by Bohlmark (2008), Van den Berg et al. (2014) and Lemmerman and Riphahn (2018), who conclude that the critical age to arrive is about six or nine.

Third, we do not find evidence that refugee age at arrival influences mental health as so far as this is reflected by the use of psychiatric medicines or use of anxiolytics. Also, we do not find evidence that

[6] Unlike Butcher and Case (1994) and later Dahl and Moretti (2008) we do not find evidence that the educational performance of girls is affected by the sex composition of her siblings.

refugee age at arrival affects expenditures on primary mental health care costs or the use of personal assistance, a type of primary health care often provided to people who require assistance in the planning of everyday life. This is in line with results by Lemmerman and Riphahn (2018), but unlike the findings of Van den Berg et al. (2014). An often mentioned explanation for this discrepancy could be that most of the refugees whom we study come from Arabic countries and it might require different skills to help people from Arabic countries compared to native people (Al-Krenawi and Graham, 2000). Also people with mental health problems with an Arab background have been reported to make less use of formal health care (Fakhr El-Islam, 2008). However, we do not think that this drives our results for mental health, as we also fail to find evidence for as relationship between mental health outcomes and age at arrival looking at refugees from former-Yugoslavia or the former Sovjet-Union.

Our results provide several important insights to policymakers. We show that refugee children who arrive at an older age will have lower educational attainment than those who arrive at a young age. This is especially true for female refugees, whose educational attainment increases the most if they would have arrived one year earlier. As we do not find evidence for a critical age after which educational attainment decreases more steeply, our results suggests to improve the educational attainment of refugee children across the age distribution. A somewhat disappointing message to policymakers is that our results also illustrate that unobserved heterogeneities at the family level are important and should be taken into account when studying refugee educational attainment.

Furthermore, many refugee children enter the destination country via family reunification.[7] These children have to remain in their home country until a residence permit has been given to the initial applicant. Our results imply that the benefits of shortening asylum application waiting times extend to the children of refugees who enter via family reunification, because it allows them to arrive at a younger age.[8] These children would benefit substantially, even if the accomplished reductions in waiting time are small: All else equal a reduction in the average asylum application processing time by only a month increases the propensity to obtain higher educational degree by about 0.3 percentage points. The large differentials in the processing time across European countries, as have been documented by Dustman et al. (2017), suggest that small reductions are feasible.

[7] For instance, more than fifty percent of children entering the Netherlands in 2016 arrived via family reunification (Statistics Netherlands, 2017).
[8] Hainmuller et al. (2016) show that asylum waiting times decrease the economic performance or refugees.

2. Inflow of refugees and the Dutch asylum procedure in the late nineties[9]

We study refugees who entered the Netherlands between 1995 and 1999 as children. In these years refugees had to apply for asylum at one of the registration centers located close to the national border or at the national airport. When the asylum application was considered promising, the asylum seeker was first sent to a research and reception center to start the asylum application. Thereafter the asylum seeker quickly moved to an asylum seekers center while the asylum application was being handled. This could take several months to several years. After being granted a (permanent or temporal) residence permit, refugees were outplaced by and large randomly across the country.[10] Refugees were allowed to let their spouse and children come to the Netherlands, but only after a residence permit had been received.

The Dutch asylum process is relatively strict compared to other European countries, also after controlling for applicant characteristics (Leerkes, 2015; Dustmann et al., 2017). Dustmann et al. (2017) report that the Netherlands granted the 'full' Geneva Convention Refugee status to about 25 percent of successful applicants in 2014, whereas this percentage exceeded 80 percent in neighboring countries Belgium, Germany and the UK. They also show that the Dutch average share of cleared applications over the years 2010-2014 was relatively low, despite the fact that inflow into the Netherlands was relatively low as well. This indicates that asylum applications in the Netherlands take longer than in other European countries.

3. Data

Between 1995 and 1999 many refugees entered the Netherlands and other OECD countries in the wake of the establishment of a totalitarian regime in Iran, the first Gulf war in Iraq and civil wars in Afghanistan, former Yugoslavia and Somalia (Maliepaard et al, 2017). In total we observe outcomes for more than 90 thousand refugees up to fifteen or twenty years after arrival, where refugee status was based on registrations by the Dutch Immigration and Naturalization Office (IND). This contrasts sharply to most of the literature that does not observe refugee status or that observes only a limited sample of refugees for a limited number of years (see Evans and Fitzgerald, 2017).

[9] A more detailed description (in Dutch) of our refugee sample and placement policy is provided by Maliepaard et al. (2017) and Gerritsen et al. (2018).

[10] An exception was made for refugees who had a job or who followed education in a specific municipality, refugees with direct family members who are already outplaced and refugees who should be placed in a municipality based on a medical indication.

We use administrative records provided by Statistics Netherlands to study the effect of age at arrival on educational outcomes and mental health for asylum migrants (‘refugees’) who were twenty or younger when they arrived.[11] The maximum age at arrival is twenty as we hardly observe any siblings among refugees who arrive at age 21. We observe children who entered the country with their parents or who followed after the first registration of the initial parent. Also, our sample might include children who were granted a residence status via a general pardon scheme or who entered the Netherlands as an invited refugee in the UNHCR resettlement program.[12] The administrative records we use provide background characteristics such as country of origin and gender. They also allow identifying sibling refugees by linking children to their parents. We augment this dataset with other administrative data sources provided by Statistics Netherlands that measure educational attainment and mental health.

The administrative records also provide the day at registration and day of birth which we use to determine age at arrival. However, age at arrival and age at registration are not necessarily equal as refugees could only register in the Netherlands if they were in the country for at least six months or if they were granted a residence permit. Hence for most refugees our key explanatory variable is measured with error. As is well known, this could lead to inconsistent estimates.[13] In the section on the empirical strategy we explain that we deal with this bias by considering only refugees who registered at the same day.

Descriptive statistics

Figure 1 shows the distribution of age at arrival for the 6,979 siblings who are observed at age 25. The figure shows that relatively young and relatively old children are underrepresented in our data: more than 80 percent of the refugees arrived at ages six to fifteen. Recall that we observe refugees who arrived at the first of January 1995 or later and that outcomes are observed until 31 December 2015, which means that four is the minimum age at arrival that we observe in our data. Table 1 shows summary statistics for sibling refugees evaluated at age 25. Slightly less than half of the refugees are female. Most refugees are from Afghanistan or Iraq, accounting for half of the

[11] Studies on the impact of age at arrival for migrants investigate migrant children who arrived at age 18 or younger. They do so as moves at later ages are considered endogenous as the child chooses to migrate instead of the parents. As refugees are forced to migrate to escape violence or persecution, we do not use this cutoff.
[12] A residence permit was granted to asylum migrants in 2007 if they entered the Netherlands before the first of April 2001 (and were still in the country). About 27 thousand asylum migrants benefit from this scheme. Also the Netherlands participates in the UNHCR resettlement program. Each year, about 500 refugees enter the Netherlands this way.
[13] See Griliches (1979) and Bound and Solon (1999).

population. It is important to realize that age at arrival could be correlated with other refugee characteristics that affect educational attainment in the destination country or mental health. Upon arrival children from Iran are almost half a year older -and Somalian children are about 0.8 year younger- compared to children from other countries (not included in Table 1). As refugee children from Iran do relatively well at school and children from Somalia perform poorly (Maliepaard et al., 2017), this underlines the importance of our empirical strategy to include family fixed effects. Without controls for the country of origin part of the positive (negative) effect of being from Iran (Somalia) on educational attainment would be attributed to age at arrival, creating an upward bias on the impact of age at arrival.

Educational attainment, mental health and of age at arrival

We study how educational attainment and mental health are affected by the age at which refugees arrive in the destination country. We measure educational attainment using an indicator whether the refugee obtained a higher educational degree at age 25. We use this measure as we do not observe other educational outcomes for cohorts born before 1988, unless they enroll in higher education.[14] We observe higher educational degrees handed out from 2002 onwards. We evaluate the mental health of refugees by studying the uptake of antidepressants and/or anxiolytics at age 25.[15] Data on use of these medicines is available from 2006 onwards, which is why the maximum observed age at arrival for this outcome equals eighteen. In the remainder of this section we illustrate graphically the (unconditional) relationship between our outcome variables and age at arrival.

The left panel of figure 2 shows how the proportion of refugees that possess a higher educational degree changes with the age at arrival. It shows that about 25 percent of the refugees obtained this type of educational degree if they arrived in the Netherlands at age eight old or younger. The propensity to hold a higher education degree falls steeply at age nine and it decreases to about ten to five percent for refugees who were fifteen or older when they arrived. The gray bars indicate that the decrease in the percentage of refugees with a higher education degree is largest at ages nine,

[14] Educational degrees are observed when they are handed out. This data is available from 2001 onwards for university degrees and from 2004 and 2005 (and later) for high school and vocational education respectively. As the latter degrees are typically obtained at ages 16 to 21, we do not observe high school or vocational education degrees for cohorts born before 1988 (2004 minus 16). In contrast we observe all diplomas for cohorts born in 1980, if we assume that refugees are at least 21 when they graduate from university (the average graduation age for refugees in our sample is 24). About ten percent of refugees is born before 1980 and about 85 percent before 1988.

[15] We did consider the effect of age at arrival on the use of other medicines, where we used LASSO and cross-validation to select medicines that are genuinely affected by age at arrival. We did not find evidence that use of medicines is affected by age at arrival if we condition on family fixed effects, see Appendix A.

thirteen and fifteen. The right panel shows how use of antidepressants and/or anxiolytics varies with age at arrival. The uptake of these medicines is increasing in the age at which refugees arrive in the country. Average use is below four percent for refugees who arrive at age nine or younger, but it more than doubles to about eight percent for refugees who enter the country at age sixteen. The largest changes in mental health, as measured by the uptake of antidepressants and/or anxiolytics, are observed for refugees who enter at age thirteen and ten.[16] Overall the two panels suggest that child refugees arriving at a relatively old age have lower educational attainment and reduced mental health than those arriving at a relatively young age.

Next, we document gender differences in the relationship between these outcome variables and age at arrival. The left panel of figure 3 shows how the propensity to obtain a higher educational degree varies with age at arrival for boys and girls. It shows that the educational performance of girls and boys is similar if they arrive at age sixteen or older. However, girls arriving at a younger age do substantially better than boys who arriving at identical ages, and the gap in educational performance between girls and boys grows when age at arrival decreases. The right hand side of Figure 2 shows how use of antidepressants and/or anxiolytics varies with the age boys and girls arrive in the destination country. At nearly all ages at arrival the use of these medicines is larger for girls than for boys. The gender gap is relatively small and stable across all ages at arrival categories, except for refugees who were sixteen or seventeen when they arrived. The figure also shows that girls who arrived at age eighteen are less likely to use these medicines compared to boys arriving at this age, but this average for girls is based on only 38 observations.

Finally, the left panel of Figure 4 illustrates how the relationship between our main outcome variables and age at arrival varies by country of origin. We single out refugees from Afghanistan, Iraq and former Yugoslavia, as they form almost seventy percent of our sample. The graph shows that a) educational attainment is decreasing in age at arrival for all subgroups considered and b) refugees arriving ate age sixteen or older have similar outcomes. As an illustration consider the difference in educational attainment at ages of arrival six and sixteen. All refugees who arrived at age sixteen have a low probability to obtain a higher educational degree, regardless of their country of origin. Yet at age of arrival six refugees from Afghanistan, Iraq and Former Yugoslavia do substantially better than refugees from other countries.

[16] There is also a big drop in the propensity to use antidepressants and/or anxiolytics at age 17. However, this number is based on fewer than 100 observations.

The right panel of Figure 4 shows the relationship between mental health and age of arrival by country of origin. This picture suggests that mental health is decreasing in age at arrival for all subgroups considered. However, there does not seem to be a subgroup with better or worse mental health across all or some ages at arrival. We also find that the use of antidepressants and/or anxiolytics varies strongly within refugees from the same country of origin. Finally, note that the uptake of antidepressants and/or anxiolytics for refugees from Afghanistan and Iraq, two countries with an Arab culture, is similar to that of refugees from former Yugoslavia for all age groups considered.[17]

4. Empirical strategy

The aim of our empirical analysis is to estimate the causal effect of refugee age at arrival on outcomes related to educational attainment and mental health. Like other studies on the causal effect of age at arrival on outcomes later in life we base our empirical strategy on the inclusion of family fixed effects. This means we compare siblings within families. This strategy identifies the age at arrival effect under the assumption that siblings fare equally well on average in the absence of a difference in age at arrival. Equation (1) provides the main specification, where Y_{ij} denotes the outcome variable of sibling *i* from family *j* measured at age 25. At this age most people have finished their school career and mental health problems should have become apparent if present. Age at arrival (AaA_i) is the main independent variable and ranges from four to twenty because of the time span of our data.[18]

$$Y_{ij} = \alpha + \beta AaA_{ij} + \gamma' X_{ij} + \tau_{ij} + \mu_j + \varepsilon_{ij} \qquad (1)$$

We also include X_{ij} to control for characteristics of refugees that vary within families, where we follow the literature and condition on gender as girls generally perform better at school. We also include an indicator for being firstborn, because educational attainment varies with birth order (Black et al, 2005). Furthermore, in august 2007 a policy reform (the *kwalificatieplicht*) was introduced that increased the compulsory school age from 16 to 18 for pupils with no or a lower secondary educational degree. This is why we extend X_{ij} with an indicator for being subject to this policy change. τ_{ij} are indicators for the year the outcome is measured. These indicators control for

[17] The dominant culture in former Yugoslavia varied strongly across regions within the country. For instance depending on the region the dominant religion could be Catholic, Orthodox or Muslim.
[18] We observe refugees who arrived at the first of January 1995 or later and our observation period ends at December 31, 2015. If we evaluate outcomes at age 21 we can observe refugees who entered at age zero (if they arrived in 1995). At age 22 the minimal age of arrival equals one, at age 23 it equals two, etc.

birth cohort effects[19], business cycles or real earnings growth over time. Finally μ_j are family fixed effects and ε_{ij} is the error term assumed to be i.i.d. As outcomes are not independent within families, we cluster standard errors at the family level.

Inclusion of family fixed effects

There are several reasons why it might be important to include family fixed effects. First, in a cross sectional setting -without these effects- one might be concerned that parents who find their children future to be important leave their country sooner, i.e. when their children are younger. In that case estimating equation (1) will give biased estimates of the age of arrival effect if the children of these parents have potential better outcomes than children of parents who postpone their migration decision. By using sibling data and including family effects μ_j we are able to control for all family factors that are shared by the siblings, like timing of the move (as is thoroughly explained in Van den Berg et al., 2014), parental education, (mental) health that is inherited from the parents, family income and home environment. The latter captures the full range of traditions, norms, values, family structure and household practices within the family. This strategy also controls for the potential endogeneity of the (duration of the) asylum process shared by refugee siblings. This is important as in a cross sectional setting the duration of asylum procedures can vary widely across families depending on the complexity of the asylum application. This is important as a longer stay in asylum centre has been found to reduce labor market performance substantially (see Hainmuller et al., 2016).

Second, under certain conditions, the inclusion of family fixed effects allows us to control for measurement error in the age of arrival variable. Recall that we define age at arrival using the day the refugee registers in the Netherlands. Refugees were only allowed to register if they possessed a residence permit or if they had been in the country for at least six months. The Dutch Immigration and Naturalization office (IND) was able to provide us the true day at arrival for about 30 percent of refugees, which shows that this subsample registered on average 242 days after arrival. This suggests that measurement error poses a real threat to our identification strategy. However, as is stressed by Bohlmark (2008) and Åslund et al. (2015), the family fixed effects eliminate the measurement error under the assumption that it is fixed within families and that age at arrival enters specification (1) linearly.[20] The assumption that measurement error is fixed within families

[19] As we measure outcomes at a particular age, the year indicators are perfectly multicollinear to birth cohort indicators.

[20] Note that the family fixed effects do not control for the measurement error when age at arrival enters equation (1) categorically. In the linear case, the age at *arrival* difference between siblings is equal to the age

seems valid as our subsample shows that 93 percent of refugee sibling who registered at the same day also arrived at the same day.

Possible flaws of family fixed effects and heterogeneous effects

We are interested in β, the average effect of age at arrival on educational attainment and mental health later in life. As said, identification of this parameter hinges on the assumption that siblings fare equally well in the absence of different ages at arrival on average. This might not be the case as girls do better in school compared to boys with the same age of arrival. Indeed the effect of age at arrival has been found to differ by gender (Bohlmark, 2008; Åslund et al., 2015; Hermansen, 2017, Lemmerman and Riphahn, 2018). This is why we allow for heterogeneous effects of age at arrival for boys and girls.

In addition the effect of age at arrival might differ by birth order. This occurs if younger children and their parents learn from the difficulties faced by the older siblings as the latter go first through Dutch institutions like the educational system. The younger children might benefit from this knowledge and this might lead to overestimation of the age at arrival effect. We therefore estimate a version of equation (1) that includes an interaction term between birth order and age at arrival, which allows us to test whether the effect of age at arrival differs between firstborn and later born children. In addition, we look at heterogeneous effects by country of origin and having lived in an asylum centre, as it can be argued that age-of-arrival effects might differ between refugees from different countries and that have experienced different living conditions upon arrival in the destination country.

When interpreting our findings, one should keep in mind that models are estimated for siblings whose parents are registered in the Netherlands. Hence, we cannot estimate the effect of age at arrival for only-children or children whose parents did not come to the Netherlands.[21] Although the family fixed effects control for measurement error that does not vary within families, their inclusion increases the problems related to measurement error that varies within families (see Grilliches, 1973 or Bound and Solon, 1999).

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at *registration* difference if siblings who arrived at the same day also register at the same day. In the categorical case however, this need not to be equal. Consider two siblings who arrive at ages two and four and assume they register exactly one year after arrival at ages three and five. In the linear case the difference in both type of measurements is equal to 2. In the categorical case, however, the difference in the age indicator for age=2 is equal to 1 (=1-0) when age at *arrival* is used, and equal to 0 (=0-0) when age at *registration* is used.

[21] These are in most cases refugees who arrived as unaccompanied minors.

Selection of covariates

In our specification we include covariates for birth order, gender and being subject to the policy reform that extended compulsory school going age from sixteen to eighteen. However, the list of control variables could be extended with other indicators for birth order or indicators for month of birth.[22] We do not include all these variables, because including irrelevant controls might lead to overfitting and insignificant parameter estimates. Instead we estimate equation using the Post Double Selection estimator (Belloni et al. 2011; 2012; 2013; 2014; 2016) and the Post Regularization estimator (Chernozhukov et al., 2015). These estimators use regularized regression and cross-validation to select a sparse set of control variables out of a high-dimensional set of potential control variables. Our high-dimensional set of potential control variables extents the controls in equation (1) with indicators for being a second born, an indicator for being third born (or higher order), indicators for month of birth and interactions between these variables and the asylum experience of the household (i.e. whether the refugee was living in a refugee facility, the number of years to be registered before outplacement and whether the refugee moved before being outplaced). Family fixed effects are always included as these are crucial to our identification. The Post Double Selection estimator and Post Regularization estimator select additional control variables besides the baseline controls for gender, being firstborn and being subject to the reform of the compulsory school age. When educational attainment is the dependent variable these estimators also select nine indicators for month of birth, an indicator for being second born and interactions between indicators for being firstborn and having moved while awaiting the asylum decision. When mental health is the dependent variable these estimators select identical controls, except that the indicators for being second born and being female are not included and an additional month of birth indicator is selected. Appendix B provides a detailed description of the Post Double Selection estimator and Post Regularization estimator applied to equation (1). Importantly, these estimators use the same identifying assumption as OLS, which is why we can use them to evaluate the robustness of the impact of age at arrival on educational attainment and mental health later in life (Athey et al., 2017).

5. Results

In the first part of this section we consider the effect of age at arrival on educational attainment and mental health if age at arrival enters linearly. We use various estimators to evaluate the robustness

[22] Month of birth has been found to drive health and educational outcomes later in life, possibly because of in-utero effects (Doblhammer and Vaupel, 2001) and/or because it changes the relative age at which cognitive tests are performed (Crawford et al., 2014). Note that our family fixed effects control for parental preferences (correlated with SES) that generate seasonal effects in the number of births (Buckles and Hungerman, 2013).

of the effect. In the second part of this section we study the heterogeneity of the estimates. Here we compare estimates of the effect of age at arrival when it enters equation (1) linearly or categorically. In addition we report how the impact of age at arrival on educational attainment and mental health varies with gender, birth order and country of origin. In the third part of this section we show the effect of age at arrival on other measures of educational attainment and mental health. These measures also allow a close comparison of our results for refugees to those found by other scholars for migrants.

Educational and mental health outcomes at age 25

Panel A of table 2 shows the effect of age at arrival on educational attainment and mental health. Without the inclusion of family fixed, we find that every year that the migration decision is postponed reduces the probability to hold a higher educational degree by 1.4 percentage points on average and the 95 percent confidence interval ranges from -2.1 to -0.7 percentage points. This estimate becomes more negative when family fixed effects are included. Now arriving one year later reduces the probability to hold a higher educational degree by 3.6 percent and the 95 percent confidence interval ranges from -6.3 to -1.0 percent. This suggests that there are variables not included in (1) that vary at the family level and place an upward bias onto the estimated impact of age at arrival.[23] We inspect the robustness of our results by estimating equation (1) using the PDS and PR estimators, two estimators that rely on the same identifying assumption (i.e. that family fixed effects control for unobserved heterogeneities at the family level). Table 2 shows that these estimators yield somewhat larger but similar results as the OLS estimator. Arriving one year later reduces the probability to obtain a higher education degree by 6.0 percentage points, where the 95 percent confidence interval ranges from -9.5 to -2.4 percentage points. Results differ from those based on OLS as the list of included controls is larger than the controls presented in equation (1).[24] Note that the 95 percent confidence intervals provided by the OLS, PDS and PR estimators overlap and none of these estimators can reject that the impact of age at arrival on the propensity to hold a higher educational degree ranges from -6.3 to -2.4 percentage points.

For mental health results are very different. In line with the observational data presented in figures 2 to 4, the impact of age at arrival on the propensity to use antidepressants and/or anxiolytics is small and has a positive sign: arriving one year later increases this propensity by 0.2 percentage points on

[23] This is also concluded by Lemmerman and Riphahn (2018) using German data. Using Swedish data Bohlmark (2008) finds that results with and without family fixed effects are similar.

[24] Additional controls are nine indicators for month of birth, an indicator for being second born and interactions between indicators for being firstborn and having moved while awaiting the asylum decision.

average, but the estimate is imprecisely estimated and insignificant. The 95 percent confidence interval ranges from -0.1 to 0.6 percentage points. In contrast, the effect becomes negative (and remains insignificant) after family fixed effects are included. The estimate equals -0.47 percentage points with a wide 95 percent confidence interval ranging from -2.4 to 1.4 percentage points. The effect on mental health changes considerably if equation (1) is estimated using the PDS or PR estimator, although the estimate remains insignificant: arriving one year later reduces the probability to use antidepressants and/or anxiolytics by 1.5 percentage points on average and the 95 percent confidence interval ranges from -4.1 to 1.1 percentage points. Again the control set used by the PDS and PR regressors is larger than the set of controls in equation (1) and it is similar to the one used when educational attainment was the dependent variable.[25] Overall, our results for mental health do not allow us to draw strong conclusions on the impact of age at arrival on mental health later in life, because a) this effect is imprecisely estimated and b) the estimates are sensitive to the choice of estimator using the same identical identifying assumptions.

Heterogeneity analysis

If age at arrival enters equation (1) linearly the family fixed effects control for measurement error of age at registration. However, this is only valid if the impact of age at arrival is genuinely linear. We therefore present estimates of the impact of age at arrival on educational attainment and mental health where age at arrival enters categorically. Figure 5 and 6 plot the estimated effects for the propensity to hold a higher education degree (figure 5) or to use antidepressants and/or anxiolytics (figure 6). We first discuss the impact of age at arrival on educational attainment. The estimated coefficients from the specification with age dummies are almost in a straight line and decrease at a similar speed with age at arrival as the linear specification. This means that the effect size of arriving one year later in the Netherlands is relatively constant over the age of arrival distribution. Related to this observation, we do not find evidence in favor of a ‘critical age’: there is no age after which the effect declines more steeply. This is in line with Åslund et al. (2015) who also do not find evidence for a critical age. Yet it contrasts with results by Bohlmark (2008), Van den Berg et al. (2014) and Lemmerman and Riphahn (2018), who conclude that the critical age to arrive is about six or nine. Their results suggest that the fact that we measure age at arrival only for refugees who were older than four when they arrived need not be the reason why fail to find evidence for the existence of a critical age. Finally, note that only the older age dummies are significant in the categorical specification, which might be explained by the fact that refugees who arrived at age four are the reference category.

[25] Indicators for being second born and being female are not selected and an additional month of birth indicator is selected.

In figure 6 we consider the linearity assumption for the impact of age at arrival on mental health evaluated at age 25. Again, the estimated coefficients under the categorical specification are centered round the impact of age at arrival under the linear specification. Thus the impact of age at arrival on mental health seems to be linear, although it should be mentioned that the effects are imprecisely estimated.

Figures 5 and 6 suggest that the impact of age at arrival on educational attainment and mental health is genuinely linear. We therefore use the linear specification to consider whether the impact of age at arrival varies by subgroups of refugees, see panel B of table 2 for results. We first consider whether the impact of age at arrival on educational attainment differs between male and female refugees. The effect of arriving one year later on the probability to obtain a higher educational degree is about 25% larger for women than for men (-0.046 versus -0.037). These differences are also statistically significant (F=6.80, p-value=0.0092), which is in line with results by Bohlmark (2008), Hermansen (2017) and Lemmerman and Riphahn (2018). Van Ours and Veenman (2006) suggest that migrating girls adapt less to the culture in the destination country than migrating boys, because they are more protected by their family. This could harm educational achievements, especially in a competitive schooling system. For mental health we find that the impact of age at arrival on mental health for boys is about forty percent larger than for girls, yet as estimates for both girls and boys are imprecise we cannot reject the null hypothesis that both parameters are equal.

Next, we split up the sample into first and later borns. A difference in the age-at-arrival impact between these groups violates the assumption that siblings would fare equally well in the absence of different ages at arrival. As it turns out, we find no statistical significant difference between the two groups for educational attainment or mental health. This suggests that younger siblings do not have better performance in school than older siblings, because they can benefit from the experience of the latter.

We also consider whether the impact of age at arrival differs by home country. As 85 percent of our estimation sample comes from only five countries, we compared whether the impact of age at arrival for refugees from Iran, Iraq, former Yugoslavia or other countries differs for the effect found for refugees from Afghanistan (the largest group). We do not find evidence that the impact of age at arrival for refugees from these subgroups differ from those for refugees from Afghanistan. Thus refugees form a relatively homogenous group compared to regular migrants, for whom large heterogeneities by country of origin have been found by Van den Berg et al. (2014) and Hermansen

(2017). We find that the impact of age at arrival on mental health varies considerably by country of origin. For instance, the effect is nearly absent for refugees from Iran on average (less than 0.01 percentage points), but equals 0.7 percentage points for refugees from Afghanistan. However, we cannot reject the null hypothesis that the effects are equal among refugees from different home countries.

Finally refugees differ from migrants as they have to apply for asylum. We therefore considered whether the impact of age at arrival on educational outcomes and mental health differs with characteristics of the asylum application. We compare refugee children who did not register living in an asylum centre to those who registered in one or many asylum centres. As these characteristics of the asylum application hardly vary within families, a difference in estimates reflect that age at arrival effects might differ with family characteristics, similar to the case in which heterogeneities with respect to the country of origin were considered. Yet we do not find evidence that the impact of age at arrival on education attainment or mental health varies according to these characteristics of the asylum application.

Other measures of educational attainment and mental health

In the final part of this section we consider the impact of age at arrival on educational attainment and mental health later in life using other measures for these outcome variables. For educational attainment we estimate the impact of age at arrival on the propensity to be enrolled in tertiary education, the type of high school degree and the (nominal) number of years of education that should be followed to obtain the highest educational degree. We evaluate the last two outcomes at age 21, as this allows to compare our results to those found by Bohlmark (2008) and Lemmerman and Riphahn (2018) who evaluate educational outcomes at ages 17 to 18 and 21.We also compare our results to those by Hermansen (2017) who evaluates the number of years of education obtained at age 31 to 34. For mental health, we consider the effect of age at arrival on expenditures on primary mental health care (in Dutch: *Geestelijke Gezondheidszorg*). These expenditures might include costs for visiting a psychologists or treatments for psychosis. We also consider the impact of age at arrival on the use of individual assistance, a type of municipal health care often –but not exclusively- given to people who have difficulties arranging their life because of mental health problems.

First we discuss the effect of age at arrival on the propensity to be enrolled in a higher educational program, see Panel A of Table 3. We find that arriving one year earlier increases the propensity to be enrolled in a higher educational track by 2.9 percentage points, although the estimate is significant at the ten percent confidence level only. Next we discuss the effect of refugee age at arrival on the type of high school degree and on completed years of education. Again we conclude that arriving at a young age is good for educational attainment of refugees as we find that arriving ten years later reduces completed years of schooling by about 1.3 years. In line with this result we find that age at arrival also affects the obtained higher educational degree. Arriving ten years earlier increases the propensity to obtain at least an upper level high school degree by 19 percentage points.[26] We do not find evidence that the propensity to drop out of high school without a degree or to obtain at most a lower high school degree are affected by the age at which refugees arrive in the country. Thus age at arrival seems to affect only the upper types of secondary school tracks.

These results are stronger than those found by other scholars. Lemmerman and Riphahn (2018) find that arriving ten years earlier increases completed years of schooling by 0.7 years for immigrants in Germany and that it increases the probability of obtaining an upper secondary school degree by 5 percentage points. Hermansen (2017) finds that arriving ten years earlier increases years of education by about 0.5 years for immigrants into Norway and Van den Berg et al. (2014) find this increases years of education by around 0.45 years for migrants in Sweden. Our results for high school educational outcomes are larger than those found by other scholars, which can be explained by the fact that we study refugees but also by differences between the destination countries and their educational systems.

Finally, we consider the impact of age at arrival on mental health later in life using other outcome measures. We find that arriving one year earlier decreases the costs for primary mental health care by about 100 euro annually, but this estimate is highly insignificant at conventional significance levels. Results on the use of personal assistance are similar to those for the use of antidepressants and/or anxiolytics: we find that arriving one year earlier increases the use of this type of health care by about one percentage point, but the estimate is imprecise and therefore not significant. Again we cannot conclude that age at arrival affects mental health if we consider expenditures on primary mental health care or the use of personal assistance. Appendix A describes we also fail to find a robust relationship between refugee age at arrival and the use of other health medicines.

In panel C of table 3 we discuss the impact of the age at which refugees arrive on income and crime. We find that the effect on log income is positive and significant at the 5% percent level. The estimated slope for log income is 0.077 with a standard error of 0.037. This effect is very large: if a

[26] Stated otherwise, arriving ten years earlier *decreases* the propensity to obtain at most a middle secondary education degree by 19 percentage points.

refugee migrates at age 18 he will earn about a 100% more than if he migrates at age 4. A reason for this perhaps surprising finding is that we measure refugee's labor market position when they are relatively young.[27] As the results on educational attainment suggest, refugees arriving at a younger age are more likely to be in education than their older siblings. This allows the older siblings to work more hours and gain labor market experience, which might be a reason why we find that older siblings earn more than younger siblings at the early stage of their labor market career. In line with this explanation, the effect of age at arrival on income becomes insignificant once we condition on hours worked.[28]

Finally we test whether age at arrival impacts the probability to be suspect of a crime at age 25. We do not find evidence that there is a relationship between refugee age at arrival and the probability to be subject of a crime as the relationship is imprecisely estimated. The parameter equals 0.8 percentage points with a standard error of 1.2 percentage points. We also considered the effect on youth crime by measuring the outcome at younger ages starting from age 14 up to and including age 20. However, the impact of age at arrival on the propensity to be subject of a crime remained insignificant. This also occurred if outcomes are pooled over several ages.

6. Conclusions

In this paper we provide the first causal estimates of the impact of refugee age at arrival on educational attainment and mental health as young adults. We find that age at arrival has a substantial impact on educational attainment: if refugees would arrive one year earlier their propensity to hold a higher education degree would increase by 3.6 percentage points. This effect is about 25 percent stronger for girls than for boys and it does not vary across the age at arrival distribution. We do not find evidence that age at arrival impacts refugee mental health, as measured by the uptake of antidepressants and/or anxiolytics, primary mental health care costs or uptake of personal assistance.

Our conclusions are threefold. First, we estimated impact of age at arrival on educational attainment is significant and meaningful. This negative relationship is robust as we find comparable estimates

[27] Indeed Hermansen (2017) finds a significant negative effect of age at arrival on log earnings equal to -0.01 and an (insignificant) effect of -0.0025 for the probability of having a job when migrants are between 31 and 34 years old (on average 7.5 years older than the age of 25 that we use).

[28] The parameter for age at arrival equals 0.0527 with a standard error equal to 0.0327. Also in line with this explanation we find that the effect gradually decreases towards zero if outcomes are evaluated at older ages such as age 30 (results available upon request).

using two other estimators using the same identifying assumption. Also, age at arrival impacts other measures of educational attainment like university college enrollment, average years of education and the type of compulsory secondary high school degree. We find that the impact of arriving one year earlier is about 25 percent larger for girls than for boys. Perhaps this occurs because refugee parents are more protective towards their daughters, who therefore come into contact with the culture of the destination country less often (cf. Van Ours and Veenman, 2006).

Second, we conclude that the impact of age at arrival on educational attainment of refugees is larger than those found by other scholars for migrants in other countries (see Bohlmark, 2008; Van den Berg, 2014 and Hermansen, 2017). And unlike these studies, we do not find evidence in favor of a 'critical age' at which the effect declines more steeply. This could be interpreted as evidence that age at arrival impacts the educational attainment of refugees more than that of migrants who arrive at the same age. However, the difference could also be explained by differences in destination country migration policies or other characteristics of the destination countries like their educational systems. We leave it to other studies to shed light on this research question.

Third, we find no evidence that age at arrival affects mental health of refugees as measured by the uptake of anti-depressants and/or anxiolytics. This effect extends to other types of mental health care, as we cannot reject the null hypothesis that age at arrival does not affect primary mental health care costs or the use of personal assistance. Estimates of the effect of age at arrival for these outcomes are imprecisely estimated and not robust to a change of estimator. All in all, this leads us to be agnostic about the impact of age at arrival on mental health.

Our study contributes to the existing body of knowledge on the economic and social integration of refugees. We show that refugee children, who arrive at a young age, will have a better educational attainment than refugee children who arrive at a relatively old age. This is especially so for girls. As resources devoted to the assistance and integration of refugees are scarce, our study helps policymakers to identify those refugees who are most at risk.

Also our study has important implications for the design of asylum applications. As the majority of children enter the destination country via family reunification, which is only allowed after an initial residence permit has been provided to the first applicant for asylum. Our results imply that these children would benefit substantially from speeding up the asylum application process, even if the accomplished reductions in waiting time are moderate: A reduction in the asylum application processing time by only one month increases the propensity to obtain higher educational degree by about 0.3 percentage points. Differentials in the processing time across European countries, as have been documented by Dustman et al. (2017), suggest that such reductions might be feasible.

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Tables and figures

Table 1 Descriptive statistics for variables used in analyses for sibling sample

	Mean	SD	N
Background characteristics			
Age at arrival		3.531	6979
Number of children in household		1.019	6979
Female	11.110	0.499	6979
Firstborn child	2.735	0.486	6979
Year of arrival	1996.6	1.390	6979
Country of origin:			6979
Afghanistan	0.274	0.446	6979
Iraq	0.230	0.421	6979
Former Yugoslavia	0.182	0.386	6979
Iran	0.112	0.315	6979
Former Soviet Union	0.053	0.224	6979
Exposed to *kwalificatieplicht*	0.027	0.163	6979
Migrated as partner/child	0.616	0.486	6979
Has been placed in asylum center	0.518	0.500	6979
Number of registered parents	1.819	0.385	6979
Outcomes at age 25			
Completed higher education	0.168	0.374	6979
Enrolled in higher education	0.272	0.445	6979
Obtained a start qualification	0.657	0.475	6581
Uses antidepressants and/or anxiolytics	0.046	0.210	5856
Receives individual assistance	0.011	0.107	1569
Employment	0.650	0.477	6979
Log income (2015 €)	9.518	0.861	6011
On welfare	0.068	0.251	6761
Suspect of a crime	0.050	0.218	4063

Table 2 Effect of age at arrival on educational attainment and mental health

		Educational attainment: Obtained a higher education degree (1)	Mental health: Uses antidepressants and/or anxiolytics (2)
Panel A: effect of age at arrival:			
method	*Family fixed effects*		
OLS	No	-0.0142***	0.00247
		(0.00362)	(0.00192)
OLS	Yes	-0.0367***	-0.00470
		(0.0136)	(0.00979)
Post double selection	Yes	-0.0596***	-0.0150
		(0.0182)	(0.0131)
Post regularization	Yes	-.05955***	-.01501
		(.01837)	(.01314)
Panel B: Effect of age at arrival for subsamples based on OLS conditional on family fixed effects			
By gender:	Males	-0.0370**	-0.00543
		(0.0147)	(0.00992)
	Females	**-0.0457*****	-0.00389
		(0.0146)	(0.00981)
By birth order:	Firstborns	-0.0434***	-0.00585
		(0.0149)	(0.0101)
	Later borns	-0.0402***	-0.00415
		(0.0147)	(0.00974)
By country of origin	Afghanistan	-0.0408***	-0.00698
		(0.0141)	(0.00995)
	Iraq	-0.0392***	-0.00396
		(0.0139)	(0.0101)
	Former Yugoslavia	-0.0333**	-0.00113
		(0.0140)	(0.0105)
	Iran	-0.0390***	-0.000438
		(0.0145)	(0.0107)
	Other	-0.0311**	-0.00631
		(0.0141)	(0.0101)
By asylum procedure:	Outplaced directly	-0.0371***	-0.00679
		(0.0137)	(0.00985)
	Lived in one asylum centre	-0.0361***	-0.0028
		(0.00136)	(0.0099)
	lived in multiple asylum centres	-0.0371***	-0.00167
		(0.0138)	(0.0102)
Observations		6,979	5,856
Households		2827	2444

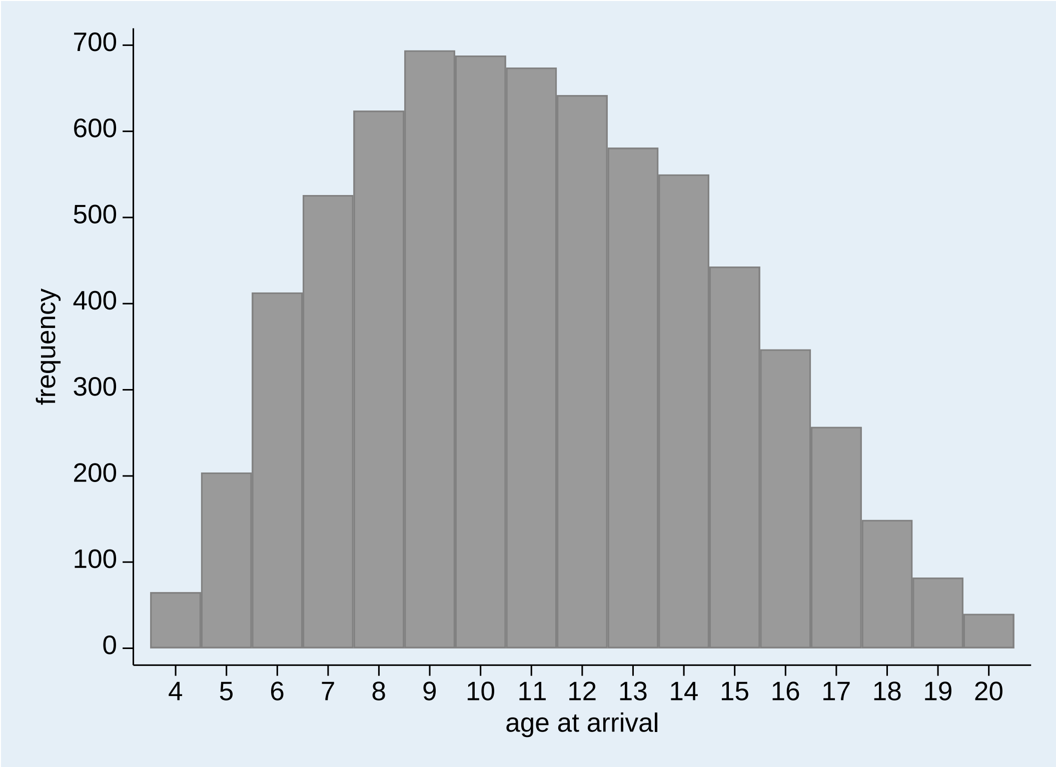
Estimated effects of age of migration on educational attainment and mental health at age 25. Reported effects for subsamples based on including interaction terms between the subgroup indicator and age at arrival. **Bold** parameters differ significantly from first-mentioned subgroup. 'asylum centre' measures the additional impact of age at arrival of being placed in asylum centre before outplacement when the refugee did not move. The parameter for 'moved while in asylum centre' measures the additional impact for refugees who were placed in an asylum centre and who moved before outplacement. Clustered standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1.

Table 3 Effect of age at arrival on other measures of educational attainment and mental health

	Effect of arriving one year later on: (1)
Panel A: Educational attainment	
Registered at university college	-0.0289*
	(0.0167)
N	6,979
Type of high school degree	
- No high school degree	0.0234
	(0.0143)
- At most a lower degree (VMBO)	0.0209
	(0.0131)
- At least an upper level degree (VWO)	-0.0194**
	(0.00941)
N	8,845
Years of education	-0.134**
	(0.0677)
N	8845
Panel B: Mental health	
Primary mental health care expenditures	104.1
	(273.7)
N	3,915
Use of individual assistance	-0.0107
	(0.00909)
N	1,569
Panel C: Other outcomes	
Log (income)	0.0767**
	(0.0366)
N	6,011
Being suspect of an offense/crime	-0.00795
	(0.0127)
N	4,063

Estimated effects of age of migration on other outcomes at age 25, except for type of high school degree and years of education that are evaluated at age 21. Clustered standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1.

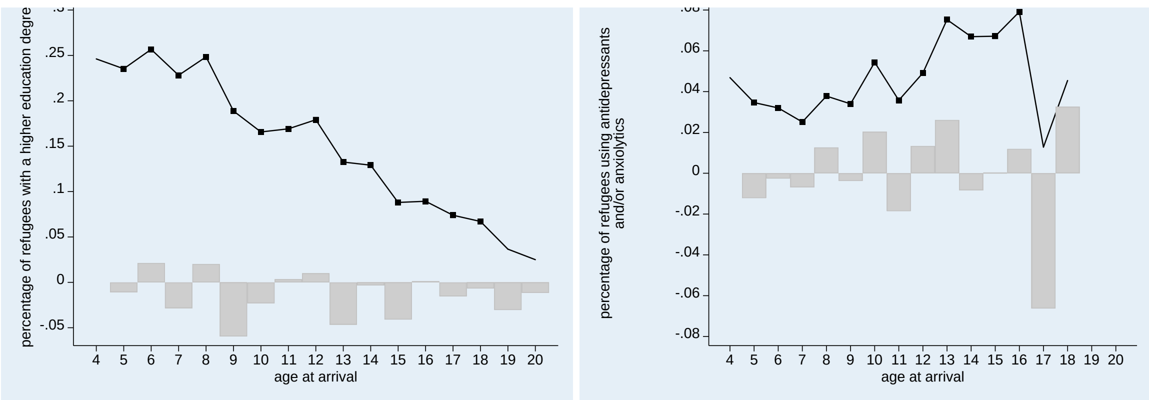
Figure 1: Age at arrival for sibling refugees observed at age 25



Notes. The histogram shows the distribution of age at arrival for the 6979 sibling refugees that are observed at age 25. The figure shows about two hundred refugees arrived at age five and about 400 arrived at age six, etc.

Figure 2: main outcome variables according to age at arrival

a) educational performance b) use of mental health care

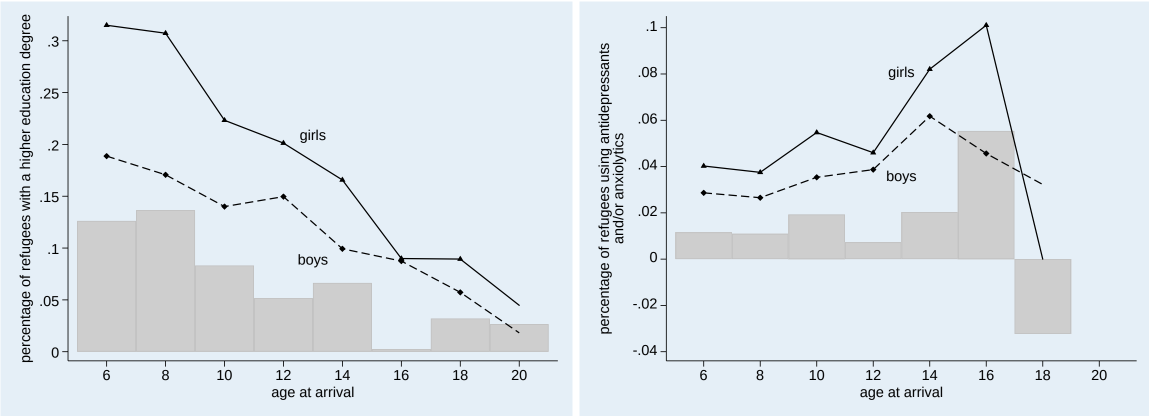


Note: solid lines represent the percentage of refugees with a higher education degree at age 25 (panel a) or the percentage of refugee that uses antidepressants and/or anxiolytics (panel b). Squares indicate the average is based on at least one hundred observations. Bars represent the change in the outcome variable compared to refugees who arrived one year earlier. Because of data availability the maximum observed age at arrival in panel b) equals 18.

Figure 3: main outcome variables according to age at arrival and gender

a) educational performance

b) use of mental health care

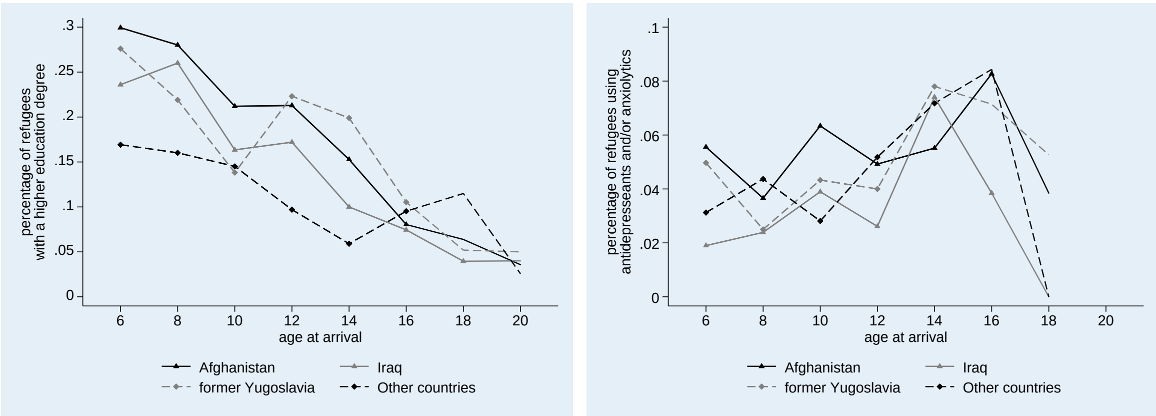


Note: solid lines represent outcomes for female refugees at age 25, dashed lines represent outcomes for male refugees. Squares or triangles indicate the average is based on at least one hundred observations. Gray bars represent the 'girl markup', the difference in outcomes between girls and boys. Because of data availability the maximum observed age at arrival in panel b) equals 18.

Figure 4: main outcome variables according to age at arrival and country of origin

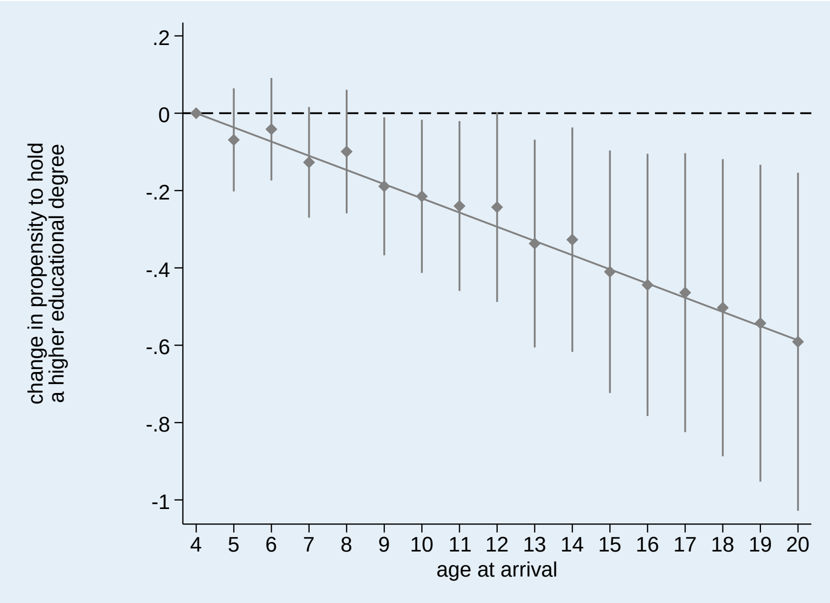
a) educational performance

b) use of mental health care



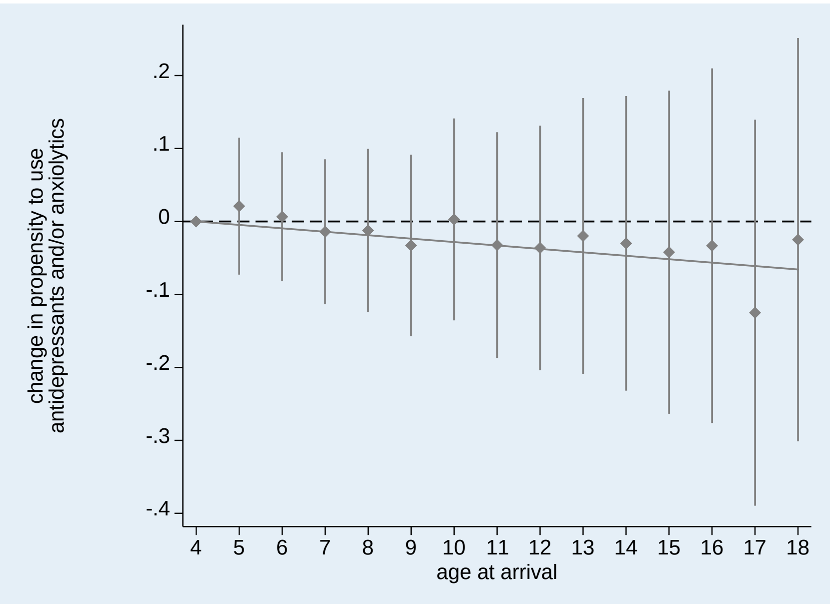
Note: lines represent outcomes for refugees at age 25, where refugees have been grouped by country of origin. Squares or triangles indicate the average is based on at least one hundred observations. Because of data availability the maximum observed age at arrival in panel b) equals 18.

Figure 5: effect of age at arrival on the probability to obtain a higher education degree



Notes. Dots: estimated coefficients of the age dummies from OLS-regression of equation (1). Solid vertical lines: 95% confidence intervals of estimated coefficients of the age indicators. Dotted horizontal line: reference category for refugees who arrived in the Netherlands at age 4. Solid declining line: effect of age at arrival from equation (1) in which age at arrival enters linearly (slope=-0.0367, se=0.0136)

Figure 6: Estimated effects of age of arrival on probability of using anti-depressants or anxyolitics, relative to a refugee who migrated age 4.



Notes. Dots: estimated coefficients of the age indicators from OLS-regression of equation (1). Solid vertical lines: estimated 95% confidence intervals for the estimated coefficients of the age indicators. Dotted horizontal line: reference category for refugees who arrived in the Netherlands at age 4. Solid declining line: effect of age at arrival from equation (1) in which age at arrival enters linearly (slope=-0.0047, se=0.0098).

Appendix A. Empirical analysis of medicine use

Using health insurance claims we observe the 202 medicines used by persons that are registered officially in the Netherlands between 2006 and 2015. The data are provided by Statistics Netherlands. Our data does include medicines prescribed by general practitioners and pharmacies (including those in hospitals), but not medicines that are part of care provided in hospitals. Medicines are defined by the 4 position ATC-code, where the first position refers to the anatomic group, the second and third positions refer to the therapeutic subgroup, and the fourth position indicates the pharmacological subgroup, see WHO (2018). For instance the ATC code N05A refers to antipsychotics, whereas the code N05B refers to anxiolytics. About forty percent of our refugee sibling sample does not use any of the listed medicines at age 25. The remaining sixty percent uses 139 medicines in total, the three that are most frequently used being anti-inflammatory and antirheumatic medicines (M01A, which makes up about ten percent of used medicines), medicines to control bacterial infections and topical inflammatory reactions (J01C and D07A, each forming about 5 percent of use).

We use the Least Absolute Shrinkage Selection Operator (LASSO, see Tibshirani, 1996) to select the medicines that are used as dependent variables in the analysis of age at arrival. The LASSO estimates parameters β such that equation (B1) is minimized. The first part of equation (B1) equals a regular error term of a regression specification equation with age at arrival (AaA_i) as dependent variable and the family fixed effects f_i and all 139 medicines used by the refugee sample as independent variables in X_i. The second parts of equation (B1) is a function of a penalty term λ and the ℓ_1 norm over the diagonal matrix Ψ containing predictor-specific penalty loadings and the parameters β. The weights in Ψ are chosen such that variables in X_i are normalized.

$$\frac{1}{N}(AaA_i - X_i'\beta - f_i)^2 + \frac{\lambda}{N}||\Psi\beta||_1 \qquad \text{(B1)}$$

The intuition behind the LASSO estimator is that the parameters β get penalized and are getting smaller as λ increases. If the value of λ gets large enough, eventually all parameters in β will be set equal to zero and no variable in X_i is included. Note that we do not penalize the family fixed effects and therefore they are always included. We do so as siblings inherit similar health characteristics from their parents and might have similar traumatic experiences while leaving their country. Also note that specification (B1) reduces the multidimensional problem of selecting the many medicines in X_i to a one dimensional problem of selecting the optimal level of λ.

We use 10-fold cross-validation to determine the optimal level of λ.[29] This application of cross-validation randomly divides the data into ten sets of approximately equal size ('folds'). We use one fold as a 'training set' and use it to estimate equation (B1) for various values of λ. This yields a set of models with varying number of medicines in X_i. For small values of lambda (i.e. specifications with many covariates included in X_i) the model most likely suffers from overfitting: it predicts outcomes in the training set very well, but performs poorly on other samples of the same data. This is why the other nine folds ('test folds') are used to compute the average mean squared error (MSE, averaged over the nine test folds). Using the test folds we select λ^{opt}, the value of λ that minimizes the average MSE. This algorithm results in a (actually not so) sparse set of 53 medicines in X_i^{opt} that are best predictors of age at arrival.

As a final step, the selected medicines are used as independent variables in equation (1). In general, we do not find evidence that age at arrival affects the uptake of medicines. However, we do find that refugees arriving at later age use more medicines that block androgens (anti-androgens, ATC code G03H) and less medicines that reduce inflammation (anti-inflammatory agents, S01B). The estimated parameter are 0.017 and -0.01 respectively and both are significant at the five percent significance level.

We detail the robustness of this result by increasing the value of λ to λ^{se}, where λ^{se} is the value of λ such that the average MSE error is just one standard error above the optimal average MSE (Ahrens et al., 2018). This reduces the number of variables in X_i, such that only the 'very best' predictors remain, at the costs of having slightly higher average MSE. If we use λ^{se}, none of the 139 medicines are included in X_i. We interpret this as evidence that the relationship between age at arrival and the two selected medicines is not particularly robust.

[29] Alternatively, the optimal value of λ could be determined using econometric theory under various assumptions (see Belloni et al., 2012; 2016) or regular information criteria like the Akaike Information Criteria (AIC) or the Bayesian Information Criteria (BIC).

Appendix B. Results using post double selection and post regularization

Post double selection method

Figure 1 shows that we observe fewer siblings arriving at young ages, which suggests refugee do not enter a destination country randomly. Consequently, we have to control for confounding effects to identify the impact of age at migration as a causal effect.[30] In equation (1) we include family fixed effects f_i to control for heterogeneities across families and refugee characteristics X_i to control for heterogeneities within families. Hence, the variables included in X_i are of crucial importance to the validity of our empirical strategy. If we leave out relevant variables the estimated parameters β might suffer from classical omitted variables bias, but the model might suffer from overfitting if we include too many variables. Overfitting creates a kind of endogeneity bias when included (spurious) controls are correlated with age of arrival, as stressed by Chernozhukov et al. (2015),

Like previous studies we control for gender and being firstborn in equation (1). Also we extent the list of controls with an indicator for the introduction of a policy that extended the compulsory school going age from 16 to 18 (this policy was only binding for pupils with a lower secondary educational degree). However, the number of potential control variables is large and could be extended with indicators for being a second born, with indicators for month of birth, or with interactions between these variables.[31] We use the post double selection method (PDS) developed by Belloni et al. (2011, 2012, 2013, 2014, 2016) to determine the variables that are included in X_i. PDS starts from the assumption that the number of potential control variables p is large, but that only a limited number of them $p^s << p$ is relevant (approximate sparsity). However, the researcher does not know the p^s variables that have to be included beforehand. PDS uses a LASSO (Tibshirani, 1996) to select two sparse sets of control variables: one sparse set denoted X_i^y includes the best predictors of the dependent variable y and a sparse set X_i^{AaA} containing the best predictors of the independent variable of interest, in our case age at arrival. PDS then uses the union of X_i^y and X_i^{AaA} as control variables in equation (1).

[30] These techniques could also be applied in setting with data from a randomized controlled experiment to gain more efficient estimates, as stressed by Chernozhuov et al. (2017a).
[31] Month of birth has been found to drive health and educational outcomes later in life, possibly because of in-utero effects (Doblhammer and Vaupel, 2001) and/or because it changes the relative age at which cognitive tests are performed (Crawford et al., 2014). Note that our family fixed effects control for parental preferences (correlated with SES) that generate seasonal effects in the number of births (Buckles and Hungerman, 2013).

Next we detail the LASSO regression. We use LASSO developed by Tibshirani (1996) to select parameters that β minimize equations (C1) and (C2). The first part of equation (C1) equals an error term of a regression specification with Y_i as the dependent variable and family fixed effects f_i and controls X_i as independent variables. In equation (C1) X_i is an extended set control variables that includes year dummies and indicators for gender, firstborn, second born, month of birth (i.e variables that vary within families). We also use interactions between these variables that vary within families and include variables regarding the asylum process that are sometimes not constant within families.[32] Note that we do not include variables that could be affected by age at arrival, as these could capture part of the effect of age at migration and therefore are 'bad controls' (Angrist and Pischke, 2008). The second part of equation (C1) combines a penalty term λ and the $\ell_1$norm over the diagonal matrix Ψ containing predictor-specific penalty loadings and the parameters β. Here the weights in Ψ are chosen such that variables in X_i are normalized. Equation (C2) is equal to equation (C1), except that the outcome variable Y_i is replaced by age at arrival (AaA_i).

$$\frac{1}{N}(Y_i - X_i'\beta - f_i)^2 + \frac{\lambda}{N}||\Psi\beta||_1 \qquad \text{(C1)}$$

$$\frac{1}{N}(AaA_i - X_i'\beta - f_i)^2 + \frac{\lambda}{N}||\Psi\beta||_1 \qquad \text{(C2)}$$

The intuition behind the LASSO estimator is that the parameters β are getting smaller as λ increases. If the value of λ gets large enough, eventually all parameters in β will be set equal to zero and no variable in X_i is included. Note that we do not penalize the family fixed effects and therefore they are always included.

As explained in appendix A, we use 10-fold cross-validation to determine the optimal levels of λ that yield X_i^y and X_i^{AaA}. As a final step we use the union of X_i^y and X_i^{AaA} as control variables in equation (1). Results using the Post Double Selection method are reported in Table 2.

Post regularization method

Cross-validation provides some protection against the inclusion of spurious control variables, but it may well lead to the exclusion of relevant control variables that have only a small effect on the

[32] Note that including year of arrival is fixed within families and is therefore dropped if family fixed effects are used. Interaction of year of arrival and individual characteristics are therefore perfectly multicollinear to the individual characteristics.

outcome. This might bias the estimation of the parameter of interest (Leeb and Pötscher, 2008), in our case the impact of age at arrival. The post regularization method developed by Chernozhukov et al. (2015) is robust to this type of specification error as it uses regression equations that are locally insensitive to this type of error. The post regularization method is closely related to the post double selection method, as a LASSO is used to determine X_i^y and X_i^{AaA}. However the post regularization method uses X_i^y to generate the residual of the outcome variable Y (i.e. the residual from a regression of X_i^y on Y_i), X_i^{AaA} to generate the residual of age at arrival (i.e. the residual from a regression of X_i^{AaA} on AaA_i) and then determines the effect of age at arrival on outcomes using a bivariate regression of the residual age at arrival on the residual outcome variable.[33] Finally, the effect of age at arrival on outcomes is determined by a bivariate regression of the residual age at arrival on the residual outcome variable. The intuition behind this method is that 'mistakes in estimating nuisance parameters are likely if we have many control variables ('high dimensions'), but that working with residualized variables makes the estimation of the average treatment effect orthogonal to errors in estimating nuisance parameters' (Athey, 2018). The residuals can be generated using the parameters from the LASSO equation directly or by using the parameters from post-LASSO OLS. [34] In table 2 we report the results using the post-LASSO coefficients.

[33]Thus this method only partials out the controls in X_i^y from Y_i and it partials out from AaA_i only the controls in X_i^{AaA}. Instead, the PDS method is equivalent to Frisch-Waugh-Lovell partialling-out the union of variables in X_i^y and X_i^{AaA} from Yi and AaA_i (Ahrens et al., 2018).

[34] Instead of using LASSO to residualize the outcome variable and age at arrival, one could use other machine learning approaches like random forests or a neural net (or a combination of them). Chernozhukov et al. (2017b) consider various machine learning estimators and show outcomes are very similar.