

The Causal Effects of Educational Policies

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April 2024

Abstract

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1 Introduction

What is the optimal age to start school? This is a question relevant from two angles. First, school systems wish to optimize the School Starting Age (SSA) as to optimize educational outcomes. Second, parents wish to optimize the age at which their children go to school given the school starting age set in the country they live in.

Bedard and Dhuey (2006) show that the youngest children in a cohort score significantly lower on tests in grade 4 and 8, and are less likely to attend university. Leuven et al. (2010) find a similar impact that an additional month of education has a positive impact on disadvantaged pupils' test scores, whereas it has no effect on not-disadvantaged students. Cook and Kang (2020) and Black et al. (2011) show similar effects for extra school enrolment on educational attainment more broadly. They additionally show more profound effects for girls than for boys. Elder and Lubotsky (2009) on the other hand find mixed results. They show that entrance age effects are more pronounced among children from upper-income families. They, conversely to other studies, find that having older classmates positively impacts test scores, but increases the likelihood of grade repetition and diagnosis with ADHD. Lubotsky and Kaestner (2016) find that children whom are older when they start kindergarten perform better on test scores. However, younger children soon catch up with their older counterparts.

From this short literature review, we identify four important mechanisms. First, younger children are less mature when entering school and do worse on tests because of this. This we call the age-on-test effect. Second, older children do better compared to the younger children which might lead to a reinforcement effect for them. They feel good about their results and gain confidence translating in a self-fulfilling prophecy. This we call the comparative-age effect. Third, the years-of-schooling effect. Fourth, the school starting age influences how much time students are given before doing these tests.

In this paper, we are ultimately interested in the fourth effect; the school starting age effect. Understanding this effect properly is obscured by the first three effects. Furthermore, these effects are at the discretion of parents, biasing OLS estimates (Ponzo & Scoppa, 2014).

As it seems that children that are old compared to their peer group perform better, parents are motivated to ensure this. They can do this in two ways. They can try to conceive at the right moment. However, this seems rather difficult. The other option is that when their child is just old enough to enter school keep them at home one more

year. This makes estimation of the effect of SSA much more difficult. Hence, we employ a fuzzy regression discontinuity design (RDD) using the birth month of students and the cutoff for school enrolment as an instrument for school starting age. We employ the same strategy as Fredriksson and Ockert (2005) by accounting for students' position in the school age distribution, given by the percentile rank in the age distribution in the school. In this manner, we tackle the confounding factor of the relative-age-effect. Through the fuzzy RDD we make sure to circumvent years-of-schooling effect. The age on test in our data is inherently covered for as the tests are all taken at the age of 15. Through this strategy, we are fairly confident to arrive at the effect of the SSA on educational attainment.

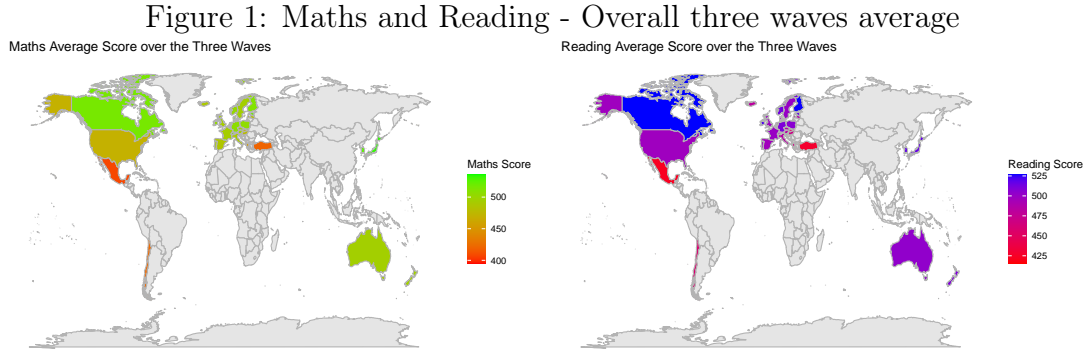
Using data from Israel, the Netherlands, and Estonia we find a significant negative impact of starting school older on educational attainment, measured by test performance. These findings seem to contradict the previous literature. However, Lubotsky and Kaestner (2016) show that younger entrants catch up after the first grade. Our results are measured in test scores at the age of fifteen/sixteen. This means that years-of-schooling for older starters is lower by definition. Hence, The comparative advantage at the start of their career due to the relative-age effect is outwayed by the years-of-schooling effect.

2 Descriptive statistics

Math and reading scores differ between countries and within countries over time.

2.1 Countries

The average of maths and reading score differ among countries (Over time in the appendix)



2.2 Over time

We compute a standardised variable that indicates the distance of each student with respect to the mean of their school in 2015. Here we take 2015 as a reference point to observe the variances over time.

$$Z_{cs} = \frac{x_{cst}^i - \bar{X}_{cs2015}}{sd_{cs2015}} \quad (1)$$

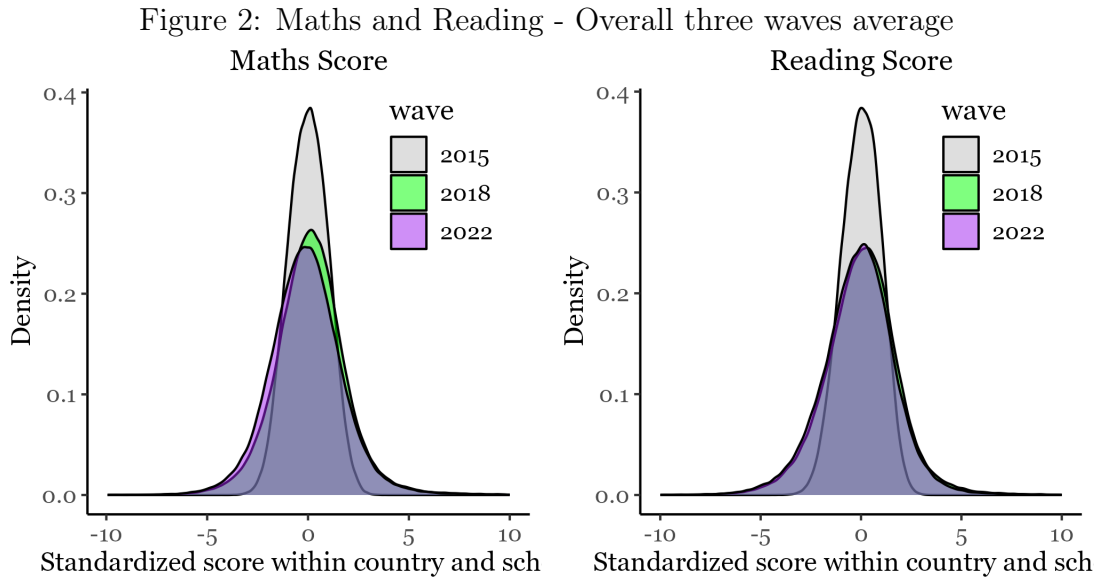


Figure 3: Caption

2.3 Intergenerational mobility

$$Z_{cs} = \frac{x_{cst}^i - \bar{X}_{cs}}{sd_{cs}} \quad (2)$$

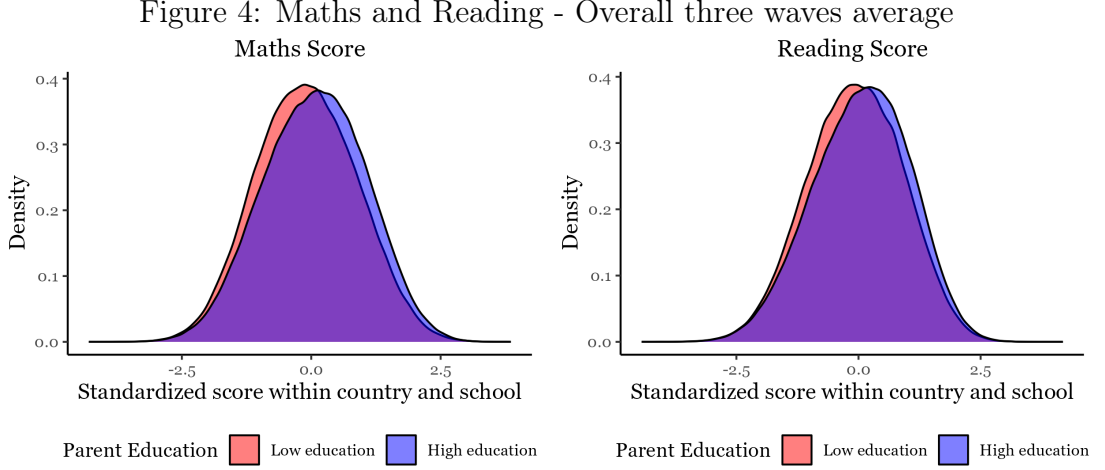


Figure 5: Caption

3 Methodology

Ideally to estimate the effect of SSA on educational attainment, we would run an RCT where we would randomise SSA between schools and make enrolment in schools not a choice at the discretion of the parents, hence also randomise this. To randomise SSA we use a quasi-experimental setup leveraging the exogenous variation in birth month. This is a fairly straightforward strategy adopted often in the literature (Bedard & Dhuey, 2006; Elder & Lubotsky, 2009; Fredriksson & Ockert, 2005). In simple terms we assume that students who are born on either side of the cutoff date are similar in background characteristics. Hence, some students receive an extra year of schooling given that our outcome measure is measured before the eventual end of schooling. So the effect of being an “old” student reflects a simulated one-year difference in school starting age. However, we have two confounders. First, the relative-age effect elaborated on in the Introduction. Second, non-compliance by students to the cutoff date. Both of these would downwardly bias OLS estimates. Hence, we use an IV estimation with the expected starting age of students as the instrument for their real starting age. As a robustness check we employ a regression where we only consider students that are born in the months adjacent to the cutoff date in a fuzzy RDD.

In short, we adopt the strategy of Fredriksson and Ockert (2005). The estimating equation becomes:

$$Y_{i,t} = \beta_0 + A_{i,t}\beta_1 + f_i^{A^S}\beta_2 + X_{i,t}\beta_3 + \varepsilon_{i,t} \quad (3)$$

which is directly copied from Fredriksson and Ockert (2005, p. 24). Where $A_{i,t}$ denotes age at test, $f_i^{A^S}$ denotes the expected age, and $X_{i,t}$ contains control variables. The expected age is constructed using the cutoff date in schooling systems. As this data is not readily available in our data, we first construct plots of the average starting age of students given their birth month. From these distributions we empirically identify countries with

a clear cutoff and use these countries for our further analysis. For the moment we take the example of the Netherlands where the cutoff date is the first of October. We would take the students born in September and in October for our analysis.

Both Fredriksson and Ockert (2005) and Ponzo and Scoppa (2014) show that some parents are more likely to plan the birth of their children in accordance with these rules. Hence, when they control for background variables related to socioeconomic position the estimates become much more precise. Like Fredriksson and Ockert (2005) we use the parents' years of education as a control for this as this is the most closely related variable available.

Finally, we use the percentile rank in the age distribution in the school to account for relative-age effects like Fredriksson and Ockert (2005). Herein, we make the assumption that this is a good reflection of the relative age compared to the classmates which is more particular than the schoolmates. However, due to data restrictions, this is the best we can do. Again, we use the expected school starting age within the expected school starting age distribution.

4 Results

In section 7.1, we present the plots of the mean starting age per month of the year per country. What we expect to see is a certain dip identifying the cutoff age. For instance, Ponzo and Scoppa (2014) show that in Italy there is a strong dip around the cutoff at the turn of the year. Given that this appears in our figures strengthens our belief that we can identify the right countries with this method. Additionally, we know from the Netherlands that the cutoff is at the 1st of October which we also identify in our plots. We see a somewhat identifiable pattern for Australia, Belgium, Canada, Chile, Denmark, Spain, Estonia, Finland, France, Greece, Iceland, Israel, Italy, Latvia, Mexico, the Netherlands, Norway, Poland, Portugal, Slovenia, and Turkey.

For the moment, we prefer to use few countries with a very clear cutoff date. We identify Israel, Estonia, and the Netherlands as the graphs with the most clearly defined cutoffs. The Netherlands and Estonia cutoff date is the 1st of October, for Israel it is 31st of August.

The construction of the expected age for the Netherlands and Estonia work the same. We use:

$$Expected_Age_i = SSA_i * 12 + Start_School_Year - Birth_Month_i \quad (4)$$

For the Netherlands and Israel SSA equals 6, for Estonia 7. The start if the school year equals 9 for all countries. Then we need to correct for children born in October, November, and December for Estonia and the Netherlands. So, they are added another 12 months. This way children born just after the 1st of October become the oldest students in their group. For Israel the children born after August are given this 12 month bonus.

In table ... we present the results of our regressions. In the first column, the OLS results are shown. The coefficient for starting age in months is negative. However, this result should not be interpreted as the causal effect. This reflects the endogeneity where the early starters are likely selected from the pool of good students whereas the late starters are selected from the pool of poorly performing students. Hence, we present the reduced form estimation of expected age on actual starting age and on reading test scores in columns 2 and 3. Column 2 shows that the relationship between expected age

and actual starting age is positive and significant. This strengthens the idea that the instrument, expected age, is relevant in forecasting the actual age. Column 3 shows that expected starting age has a negative and significant impact on test scores. In column 4, we show the second-stage IV estimation. Here, the negative, significant sign remains. This is contrary to most of the literature. As the outcome variables are taken at a given age (namely 15), it could be the case that older children, when they start schooling, simply have less years of schooling when performing the test. If this effect outweighs the comparative-age effect at the age of 15, this could be unified with previous literature. For instance, Lubotsky and Kaestner (2016) find that younger children quickly catch up with older children on test scoring. In column 5, we present the IV-regression for only children born in September and October representing our RDD specification. Again, the estimate for estimated age on test scores is negative and significant.

4.1 Starting school and tests performance

Here we show how the math and reading test scores of students correlate with the mean school starting age of primary school across countries. We calculate the average starting age of primary school for each country in each wave.

	Math	Maths ^a	Reading	Reading ^a
Average school start	2.054 (5.095)	-0.460 (5.078)	-7.017 (4.337)	-9.108** (4.159)
Constant	474.1*** (30.90)	2,005** (955.8)	529.6*** (26.30)	1,378* (782.9)
Controls	No	Yes	No	Yes
Observations	100	97	100	97
R-squared	0.002	0.152	0.026	0.206

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 1: Caption

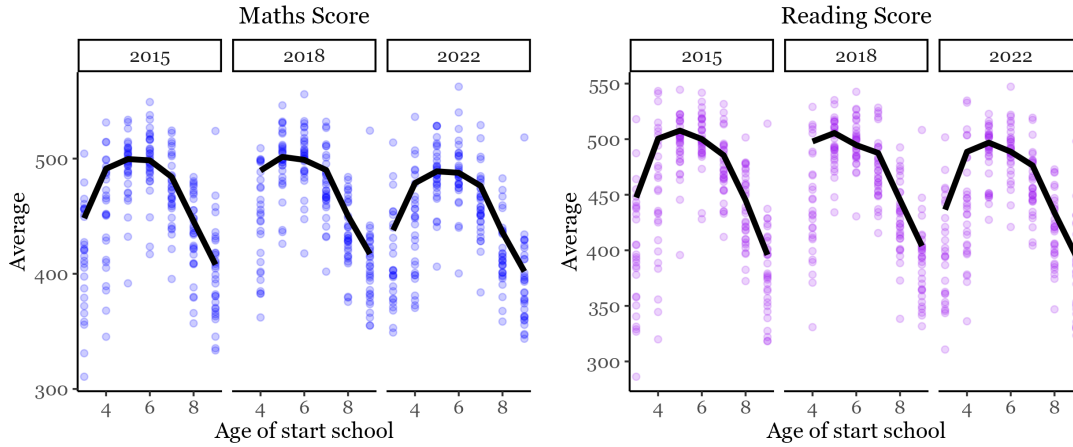


Figure 6: Starting school and tests performance

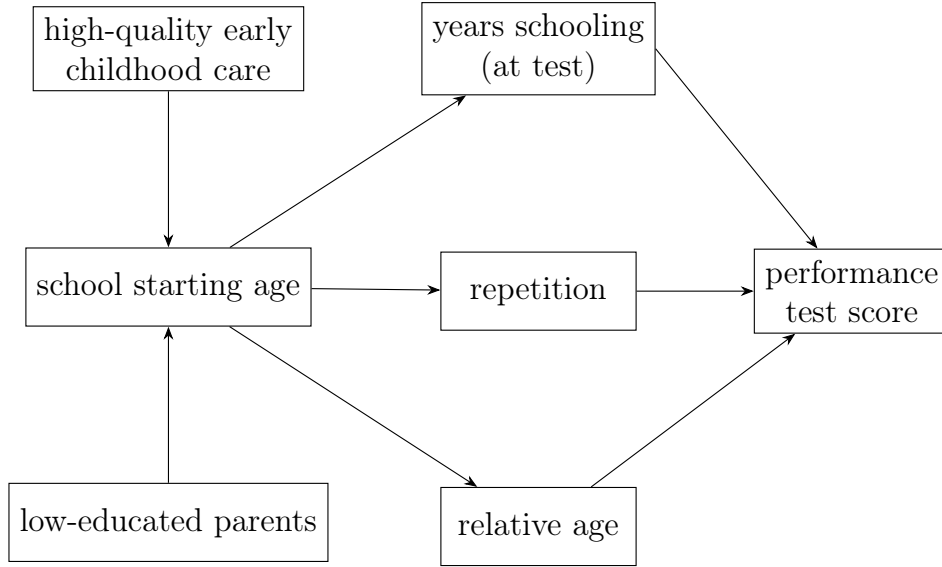


Figure 7: Directed acyclic graph (DAG)

5 Mechanisms and heterogeneity

In this section we discuss the mechanisms through which the school starting age can affect performance in maths and reading test.

We then estimate a linear regression as expressed in equation ??

$$score_{cst}^i = \alpha + \beta_1 RelAge + \beta_2 YearSchool + \beta_3 Repetition + \beta_4 SchoolStart + \beta_5 LowEduc + \beta_6 ChildCare + \tau_T + \gamma_c + \eta_s + \varepsilon_{cst}$$

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)
	mean_math_score	mean_math_score	mean_math_score	mean_read_score	mean_read_score	mean_read_score
relative_age	-37.45*** (2.339)	-36.61*** (2.299)	-36.49*** (2.298)	-39.54*** (2.718)	-38.79*** (2.693)	-38.68*** (2.692)
yearschool	42.63*** (2.154)	42.24*** (2.115)	42.14*** (2.115)	43.90*** (2.507)	43.55*** (2.482)	43.45*** (2.483)
repeat1	-64.03*** (0.807)	-62.29*** (0.810)	-62.18*** (0.811)	-71.74*** (0.964)	-70.18*** (0.969)	-70.08*** (0.970)
4.schoolstart	65.10*** (3.131)	64.93*** (3.092)	64.66*** (3.099)	73.51*** (3.745)	73.36*** (3.721)	73.11*** (3.727)
5.schoolstart	128.8*** (4.722)	128.3*** (4.646)	127.5*** (4.653)	139.3*** (5.557)	138.8*** (5.510)	138.1*** (5.516)
6.schoolstart	173.2*** (6.746)	172.5*** (6.630)	171.4*** (6.636)	185.5*** (7.880)	184.8*** (7.809)	183.9*** (7.814)
7.schoolstart	200.1*** (8.909)	199.3*** (8.754)	198.2*** (8.758)	213.9*** (10.38)	213.2*** (10.29)	212.3*** (10.29)
8.schoolstart	211.7*** (11.08)	210.7*** (10.88)	209.7*** (10.88)	225.5*** (12.90)	224.7*** (12.78)	223.7*** (12.78)
9.schoolstart	240.2*** (13.16)	237.9*** (12.93)	236.9*** (12.94)	243.1*** (15.34)	241.0*** (15.21)	240.1*** (15.21)
low_educ		-23.07*** (0.477)	-22.90*** (0.477)		-20.60*** (0.555)	-20.45*** (0.555)
childcare_d			-3.075*** (0.594)			-2.783*** (0.690)
Constant	-101.0*** (27.63)	-87.11*** (27.12)	-84.47*** (27.13)	-113.2*** (32.15)	-100.8*** (31.84)	-98.44*** (31.85)
Observations	741,467	741,467	741,467	741,467	741,467	741,467
R-squared	0.367	0.380	0.380	0.314	0.323	0.323
FE country	X	X	X	X	X	X
FE time	X	X	X	X	X	X
FE school	X	X	X	X	X	X

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

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6 Conclusion

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7 Appendix

	All Waves		2015		2018		2022	
	Maths	Read	Maths	Read	Maths	Read	Maths	Read
Australia	486.9 (89.2)	497.7 (102.1)	482.8 (87.8)	491.6 (98.1)	490.7 (85.2)	502.9 (105.4)	487.2 (94.6)	498.8 (102.2)
Austria	497.5 (87.6)	485.8 (95.6)	498.9 (87.8)	486.0 (94.2)	502.0 (86.4)	487.1 (95.7)	490.9 (88.2)	484.0 (96.9)
Belgium	505.4 (91.3)	493.5 (96.5)	510.3 (91.3)	501.8 (93.8)	510.8 (89.4)	495.5 (98.7)	494.0 (92.3)	481.7 (96.2)
Canada	497.2 (84.0)	504.0 (95.5)	504.5 (78.6)	514.1 (84.9)	503.5 (82.8)	508.6 (98.2)	484.5 (88.2)	490.5 (100.0)
Chile	435.3 (80.5)	470.1 (87.3)	442.2 (83.5)	475.5 (83.5)	434.6 (80.9)	469.4 (90.2)	428.6 (76.0)	465.1 (87.6)
Czech Republic	505.5 (90.4)	501.8 (96.3)	502.6 (87.2)	498.4 (97.0)	515.7 (89.7)	506.9 (97.2)	499.4 (92.8)	500.3 (94.7)
Denmark	491.9 (79.1)	484.6 (88.6)	497.6 (78.5)	487.3 (85.3)	497.3 (77.8)	488.1 (91.2)	478.8 (79.9)	477.2 (88.6)
Estonia	518.6 (76.9)	519.0 (85.3)	520.8 (74.5)	520.8 (81.8)	523.5 (74.6)	523.3 (89.7)	512.7 (80.3)	513.8 (84.3)
Finland	493.5 (83.7)	502.2 (99.5)	511.9 (75.7)	527.6 (87.5)	507.5 (75.7)	520.3 (96.1)	475.3 (88.4)	477.5 (101.8)
France	483.4 (91.5)	484.2 (104.8)	496.6 (89.3)	503.7 (105.2)	487.0 (91.9)	483.8 (102.6)	468.2 (90.9)	467.0 (103.3)
Germany	496.3 (88.8)	498.7 (98.8)	508.7 (83.4)	512.2 (92.9)	502.2 (90.1)	500.2 (102.8)	477.7 (90.2)	483.0 (98.9)
Greece	449.3 (80.9)	459.2 (90.6)	461.7 (81.4)	476.8 (88.4)	454.2 (80.4)	460.6 (93.3)	433.5 (78.5)	442.5 (86.7)
Hungary	483.9 (86.5)	480.0 (92.4)	484.7 (86.1)	477.3 (89.8)	488.1 (84.2)	482.9 (93.8)	479.7 (88.5)	480.0 (93.4)
Iceland	480.9 (85.4)	463.9 (98.5)	488.8 (85.7)	482.4 (92.7)	494.8 (82.8)	473.3 (101.1)	459.3 (83.5)	436.0 (95.4)
Ireland	498.4 (74.4)	518.5 (83.8)	503.4 (74.4)	520.7 (81.1)	499.6 (72.0)	517.7 (87.2)	492.2 (76.4)	516.9 (83.0)
Israel	464.7 (99.5)	475.9 (113.7)	471.6 (96.4)	482.3 (106.5)	465.0 (100.0)	472.3 (120.5)	457.1 (101.6)	473.1 (113.5)
Italy	490.1 (84.8)	485.0 (86.9)	499.8 (83.9)	492.9 (83.9)	495.1 (84.4)	481.1 (91.1)	474.0 (83.8)	480.7 (84.8)
Japan	531.3 (84.2)	511.7 (90.3)	532.5 (82.2)	516.3 (85.8)	526.6 (80.4)	503.5 (94.0)	534.9 (90.1)	515.1 (90.8)
Korea	527.5 (96.2)	516.8 (94.0)	523.4 (92.7)	516.7 (90.1)	527.5 (93.2)	515.7 (97.9)	531.1 (101.8)	518.0 (93.2)
Latvia	486.9 (72.8)	479.5 (82.4)	484.2 (70.4)	488.9 (77.4)	493.7 (71.7)	476.2 (85.7)	482.6 (75.7)	474.3 (82.6)
Mexico	408.7 (67.7)	424.4 (76.2)	413.2 (67.2)	429.0 (71.2)	415.6 (68.9)	427.6 (78.7)	395.4 (64.8)	415.2 (78.4)
Netherlands	506.4 (94.1)	481.1 (104.4)	513.9 (86.5) ^{XI}	505.0 (95.8)	514.1 (90.2)	479.8 (102.9)	491.0 (103.1)	456.8 (108.6)
New Zealand	490.9 (89.1)	506.4 (101.4)	495.8 (85.8)	510.0 (98.5)	496.4 (86.0)	508.2 (102.5)	478.9 (94.8)	500.6 (102.5)

7.1 Countries starting age plots

